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ABSTRACT

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by

TIMOTHY J. LANDVOGT

Chairperson: Professor Ali M. Kutan

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How Rational Are Inflation Expectations? A Vector Autoregression Decomposition of Inflation Forecasts and Their Errors

by Timothy J. Landvogt, Bachelor of Science

A Thesis Submitted in Partial
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CHAPTER I

INTRODUCTION

Statement of Topic

One of the important cornerstones to economic theory is that in regard to prices, expectations are rational. This means that in the long-run, expectations of price movements and therefore forecasts of inflation should be equivalent to actual inflation such that any observed difference between the two is a white noise process with zero mean and constant variance. Empirical studies in the literature present mixed results pertaining to inflation forecasts and the rational expectations hypothesis (REH). This is due to differences in issues such as data selection, modeling techniques, evaluation criteria, and forecast process assumptions or some combination of these. With the abundance of evidence both for and against REH, it is highly unlikely that a single piece of research work will ever unequivocally prove or disprove the hypothesis.

This study is no exception in that regard. It does not offer an unarguable resolution for the on-going debate regarding rational expectations (RE) that was sparked by the work of Muth (1961) over four decades ago. It does, however, attempt to shed some fresh light on the possible causes of perceived inefficiencies in the forecasts of prices. The focus of this study is *not* to determine whether inflation forecasts are rational in a black or white sense. Such an attempt would be futile, because the RE debate goes far beyond whether or not a particular model passes the statistical criteria of a well-formulated test. Instead, this paper explores the gray area created by research up to this point to determine what, if any, macroeconomic variables might explain what Ball (2001) refers to as "near rational"

behavior.[1] The study is focused on the forecast errors of inflation and implements a multivariate vector autoregression (VAR) model with a hypothetical information subset of macroeconomic variables to analyze the magnitude and persistence of apparent inefficiencies. The variables included in this subset are real GDP, money supply, unemployment, short and long term interest rates, the output gap, and a the relative price of energy. The use of the term hypothetical is necessary, because without knowing what public and private information variables comprise individual forecasters' models, this study can only make general inferences about the surveys' aggregate data. Therefore, the results should be interpreted with a note of caution, since they are generalizations of the behavior of aggregate forecast errors and should not be interpreted as evidence of *inefficiency* at the *individual level*.

Rational Expectations Explained

What does the term *rational expectations (RE)* mean in the context of inflation forecasting? A definition is necessary before describing the econometric mechanics of testing its existence. This is best done by relating the three tenets of RE--unbiasedness, efficiency, and uncorrelated errors--to a forecast that each of us consciously or unconsciously evaluates on a daily basis, the day's forecasted high temperature. Consider a simple analogy of price forecasts to a meteorologist's predictions about the high temperature for the next day. A "*rational*" weather forecaster will predict the next day's high temperature nearly right on average over time. Presuming that the livelihood of the forecaster depends on the accuracy of his forecasts, he has an incentive to be as accurate as possible given the resources and information available. The forecasts may be high on some days and low on others, but

[1] Specifically Ball (2001) shows that although forecasters use data regarding output growth efficiently, they tend to ignore other macroeconomic variables.

on average, they will *not* be consistently or predictably wrong in either direction for an extended period of time. If the forecasts *are* consistently wrong, one might call this particular meteorologist's forecasts "*biased*". The public would quickly lose faith in a forecaster who is consistently wrong and would no longer plan their outdoor activities based on these *biased* predictions. This same concept holds true regarding the rationality of price forecasts. A rational price forecaster is *unbiased* such that on average, deviations of forecasts from the true price level, called forecast errors, will have a mean of zero. Unbiased forecasts also imply a constant variance of the errors. This means that the magnitude of the errors will not vary over time. For instance, if a meteorologist normally has errors that are in a range of two degrees high or low, this range of errors, which is simply the error variance, should not change over time. This encompasses the first tenet of RE as it applies price forecasts – *unbiasedness*.

We also expect the *rational* weather forecasters to use all the information at his disposal to ensure predictions are accurate (i.e., knowledge of past temperatures for the same time of year, current conditions, movement of current weather systems on radar, etc.). This describes the second tenet of rational expectations, which is referred to as *efficiency*.[2] If a meteorologist fails to take into account some of the information available (i.e., the expectations of cloud cover or forecasted jet-stream path) on a consistent basis, then his forecasts are *inefficient* in the sense that a more accurate prediction could have been made by incorporating such information. The same standard of information usage is applicable to price level forecasters. An *efficient* price forecaster uses all public and private information

[2] RE literature repeatedly refers to full information usage as *efficiency*, but according to statistical definitions, exhaustion of the information available is more properly called *sufficiency*, which implies that no other estimator computed from the same sample can provide additional information about the parameter. Statistical efficiency refers to an estimator that has the minimum constant variance of all available unbiased estimators. To avoid confusion, this study adopts the economic literature definition.

available in generating forecasts of future price levels. In the event that the forecaster ignores or fails to correctly use information that would have reduced his forecast error, he is deemed *inefficient* and, therefore, in violation of RE. Note that by the nature of its definition, inefficiency is only identifiable *ex post* forecast.

Finally, RE implies that the forecast errors are not correlated with past errors or any information, public or private, available to the forecaster at the time that the forecast was made. In the case of our temperature forecast analogy this means that if a meteorologist regularly over-estimates by five degrees whenever it is cloudy, we would expect to see some correlation between cloudy days and historical forecast errors. A rational forecaster would realize this error and adjust future forecasts to account for these past mistakes on cloudy days. This is true with rational price forecasts as well. Any correlation of errors with past forecast errors or information available at the time of their forecast implies inefficient forecasts. Such correlation represents information that could be exploited to improve the accuracy of the forecast. Summarizing the three tenets of RE as they relate to price forecasts:

1) Rational forecasts are *unbiased* such that the forecast error has a mean of zero and constant variance over time.
2) Forecasts are *efficient* in that all publicly and privately available information is included in a model to develop the forecast, which has the smallest constant variance of all unbiased forecasts.
3) Forecast errors are *not correlated* with past errors or the information set used to create the forecast.

If a forecast does not meet any or all of these criteria, then testable evidence exists that may refute RE, if not completely, then at least to the extent that expectations are *weakly rational*. In order to show how the three criteria are empirically tested, the discussion requires an explanation of a simple linear regression model of inflation and its forecasts.

Assessing RE in a Simple Econometric Model

The analogy above provides the framework for understanding the REH as it relates to inflation forecasts, but it is not possible to empirically test the criterion without an econometric model to evaluate the forecasts. Consider a simplified version of the classic single equation linear model specification used to test RE:[3]

$$p_t = \beta_0 + \beta_1 p_t^e + \beta_2 X_{t-1} + \varepsilon_t \qquad (1)$$

Where p_t = actual price level at time t

p_t^e = forecasted or expected price level at time t

X_t = the set of publicly available information that was available when the forecast was made (usually at t-1 or earlier depending on the release date of the data)

ε_t = the error term

In this specification, it is possible to test for bias in the forecasts by setting the coefficient of the information variables, β_2, equal to zero and testing the null hypothesis H_0: $[\beta_0, \beta_1] = [0, 1]$. Theory implies that forecasts should track actual inflation one for one on average and any other informational variables, as well as the constant, should be irrelevant. Following the same logic, a *joint* test of bias and efficiency is accomplished by adding one or more explanatory variables in the information set and testing the coefficient restrictions of the null hypothesis H_0: $[\beta_0, \beta_1, \beta_2] = [0, 1, 0]$.[4]

There are two known problems of using this specification to test RE in the context of this study. The first involves the use of aggregate sample data rather than individual

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[3] This specification, originally proposed by Lucas (1978), is used to empirically test RE in both Shuh (2001) and Croushore (1998), among others.

[4] As described in Shuh (2001), page 38.

forecasts to do the hypothesis testing. The parameter estimates are subject to aggregation bias of unknown degree because the model implicitly assumes the same collective bias and efficiency exists for all individual forecasters, an assumption that is not likely true.[5] The literature review chapter contains an explanation as to why this does not constitute a critical error in the methodology of this study. The second problem is the model's inability to account for private information used by individual forecasters, because testing is done with the aggregate or consensus forecasts. Notice that the private information variable matrix does not even exist in the specification above and is probably different for each individual forecaster.

These two problems make the bivariate results subject to the same criticisms as those outlined in Bonham and Cohen (2000).[6] Despite these inherent problems, the simple bivariate regression model is used to further the works of Shuh (2000) and Croushore (1998), which both used *annual* data. Conversely, the data is examined *quarterly* in this study to identify potential inefficiencies and then explore the dynamics in detail with the multivariate VAR. Recall in the opening of this paper that validation or invalidation of the REH is not the primary goal of this study, but rather a means of focusing our discussion on which macroeconomic variables explain any perceived inefficiencies within inflation forecasts. The problems addressed above certainly cannot be ignored, but the use of panel data in the multivariate VAR specification is outside the scope of this study and left to future research.

Initial Hypotheses

The following comprise the initial hypotheses, each of which guides the study towards an explanation of inefficiencies as opposed to a direct test of RE.

[5] Keane and Runkle (1990) show that use of aggregate or consensus data causes bias in RE modeling and can lead to invalid hypothesis tests.

H_1: Inflation forecasts exhibit a significant degree of inefficiency in the use of known publicly available information.

H_2: Innovations or unforeseen shocks to some macroeconomic variables have significant and persistent impacts on inflation forecast errors.

H_3: Past forecast error disturbances dominate any measurable effects of shocks to other macroeconomic variables in explaining the variance of forecast errors of inflation.

Thesis Roadmap

This final section of the introductory chapter outlines how the remainder of the study is organized. Chapter II provides a brief review of recent literature that uses similar methodology to test the REH and explains how this paper will build upon the work presented in each of the articles. Chapter III describes the methodology of this study and the process used in variable selection for the VAR model. It also contains an overview of the data and its sources, along with any sampling conventions and special constructions necessary to make the data usable in the VAR model. Chapter IV provides detailed empirical results, including the single equation variable testing, unit root testing of explanatory variable VAR candidates, and the reduced form VAR regression results. Further analysis in this chapter includes a calculation of the impulse response functions (IRF) and variance decompositions of inflation forecast errors, as well as an interpretation of the results. Chapter V summarizes the results and draws conclusions about the initial hypotheses. It also outlines potential policy implications and suggests areas for future research on this topic.

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[6] Bonham and Cohen (2000) show that micro-heterogeniety tests confirm that the use of aggregate data in tests of REH are subject to substantial bias.

CHAPTER II

REVIEW OF LITERATURE

Theoretical Orientation

RE has long been a prominent issue of empirical analysis in economics dating back to the original ideas of Muth (1961) and later with such notable economists as Friedman (1968), Lucas (1972), and Sargent and Wallace (1976). Lucas (1972) was the first to apply a mathematical representation to the REH and test it empirically. As the accumulated historical forecast data has grown, so too has the quantity and breadth of RE literature. This is not surprising considering the many models that use RE as a foundation and the myriad of policy implications that its assumptions potentially affect within the economy.

The reason for the increase and continued prominence of RE research is an arguable topic. In fact, if ten different economists were asked why RE is so popular in modern analysis of macroeconomics, there may very well be ten different answers given. Despite the large amount of time and effort devoted to research in this area, a troubling mystery still surrounds the persistence of inflation -- a persistence that appears to have fooled forecasters again in recent years. This is evidenced by under-predictions of inflation for a span of twelve out of thirteen quarters ending in the first quarter of 2001[7]. Ironically, the onset of this trend of errors began exactly one quarter after a speech in which Federal Reserve Chairman Alan Greenspan said: "Forecasts of inflation and of growth in real activity for the United States, including those of the Federal Open Market Committee, have been generally off for several years. Inflation has been chronically *over-predicted* and real GDP growth *under-predicted*."[8]

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[7] According to the consensus quarterly forecast data contained in the ASA-NBER Survey of Professional Forecasters.
[8] Quoted as cited in Shuh (2001) page 36.

Recent Forecast Error Literature

Two recent pieces that apply particularly well to the focus of this study are that of Croushore (1998) and Shuh (2001). Both articles examine rational expectations in the classic sense by testing for bias and inefficiency using a battery of statistical methods. Croushore (1998) examines three of the most popular surveys of inflation (Livingston, ASA/NBER SPF, and Michigan Survey of Consumer Expectations). Shuh (2001) focuses on the ASA/NBER Survey of Professional Forecasters (SPF), Wall Street Journal (WSJ), and Blue Chip Economic Indicators (BC). The difference between the two is that Shuh's (2001) survey choices consist wholly of *professional* forecasters who are compensated based on accurate forecasts, whereas Croushore (1998) also looks at two surveys whose respondents do not necessarily have a financial stake in the accuracy of their forecasts.[9] Perhaps Shuh (2001) made his sample selection based on the logic posited in Keane and Runkle (1990) in which they too only considered *professional* forecasts in their sample.[10] Regardless of his rationale, this study recognizes the importance of both types of survey data and includes data from the SPF as well as the Livingston survey. The decision to use both types enables an assessment of the differences in forecast performance and information usage by the two different groups of forecasters.

Shuh (2001) does not focus solely on forecast errors of *inflation,* as done in this study, he also examines forecast errors of output growth, unemployment, and interest rates. His work includes the CUSUM test for bias, ordinary least squares (OLS) parameter significance tests similar to those described in the introduction, tests for correlation of

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[9] Expected financial compensation and the accuracy of forecasts were examined empirically in Laster, Bennett, and Geoum (1998).

[10] Keane and Runkle (1990) justify this rationale on the subjective reasoning that agents other than those who "report to the survey the same forecasts they sell on the market" (i.e. academic respondents) may have little incentive to provide accurate forecasts, and therefore not reflective of their true expectations.

forecast errors, and recursive OLS forecast simulations to test whether the additional informational variables improve (decrease) the average forecast error of inflation and growth. He claims that contrary to most previous studies of average forecasts (although none are specifically cited), forecasts are unbiased over the past three decades, but do exhibit some degree of inefficiency.[11] In particular, he finds inflation forecast inefficiencies relating to past information of unemployment and interest rates. Additionally, his results show correlation between the forecast errors of inflation and those of output growth and unemployment.

Using these findings to construct a backward looking model modified for these inefficiencies, Shuh creates a simulated forecast for the recent years of poor forecasts (1996-2000). The results for his simulated inflation forecasts are not encouraging. Although the error variance is reduced by 40-50%, the simulations actually *increase* the average forecast error in most cases. These results inadvertently leave the methodology open to criticism because the variance of actual forecast errors decreases dramatically after 1983 and then again after 1991 suggesting that there may be a structural break in the data and/or data-generating process. By using the full sample of data from 1969-1995 to construct out of sample forecasts, a strict backward looking model assumes that the past is the best predictor of future uncertainty, which may or may not be true.[12]

In contrast to Shuh, Croushore (1998) is far more concerned with the issue of bias rather than efficiency. As stated above, his research looks at forecasts made by professionals (SPF) and forecasts that also contain *non-professional* agents (Livingston and Michigan Surveys). If one were to expect the presence of bias in forecasts, logic dictates that it would

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[11] Shuh (2001) cites the longer sample period as a probable cause for the disparity between his results and those of previous studies.

[12] In particular, Ball (2000) favors a combination of backward and forward-looking models to generate forecasts, which is tied to his notion of "near rationality".

be more prevalent in non-professional forecasts where the cost of being inaccurate does not translate into an economic loss to the forecaster. However, Croushore (1998) finds little evidence of bias in either type of survey except when the sub-sample is restricted to pre-1983. In fact, he also finds that inclusion of data with updates to the present day actually eliminates the statistical significance of earlier bias tests by Turnovsky (1970) and Brown and Maital (1981), both of which found evidence refuting RE. This reversal of conclusions is due to the relatively low forecast errors of the later 1980's and most of the 1990's.

Croushore (1998) also generates an out of sample forecast by modeling historical data and is able to diminish the measurable bias (seen as a reduction in root-mean-squared forecast errors) in each of the three surveys, but only significantly in the Michigan Survey. These results fit the logic posited regarding professional versus non-professional forecasts and bias levels detailed above. The author devotes the remainder of the study searching for evidence of what he terms *optimality* in forecasts. He does so by employing several tests (sign, Wilcoxon signed-rank, zero-mean and the Dufour test) of the descriptive statistics and structure of the errors without ever addressing the subject of using additional explanatory variables to test for efficiency. His conclusions are that, in general, recent forecasts are more accurate than those measured by the first round of RE literature in the 1980's (citing the oil shocks of the 1970's as the main cause of bias), but there is certainly room for improvement using bias modified regressions.[13]

Testing Rational Expectations in a VAR Model

Univariate and bivariate linear regression models like those employed in Shuh (2001) and Croushore (1998) are not the only specifications where OLS can be used to test RE. A

[13] Croushore (1998), page 15.

number of recently published studies implement a vector autoregressive (VAR) approach to testing RE criteria using the existence of cointegration as a test for weak rationality. One such article, Grant and Thomas (1999), serves as the foundation for the VAR analysis done in this study.

Some background of Grant and Thomas (1999) is helpful in explaining their approach, which was relatively straightforward. Using both the Livingston and Michigan series and testing for stationarity of the error process, they establish *weak-form* rationality for inflationary expectations at a 10% level of statistical significance with the following VAR augmented by an error correction component:

$$\Delta\pi_t = \delta_\pi(\pi_{t-1} - \beta\pi^e_{t-1}) + \Sigma a_{11}(i)\,\Delta\pi_{t-i} + \Sigma a_{12}(i)\,\Delta\pi^e_{t-i} + \varepsilon_{t\pi} \quad \delta_\pi < 0 \qquad (2)$$

$$\Delta\pi_t^e = \delta_{\pi e}(\pi_{t-1} - \beta\pi^e_{t-1}) + \Sigma a_{21}(i)\,\Delta\pi_{t-i} + \Sigma a_{22}(i)\,\Delta\pi^e_{t-i} + \varepsilon_{t\pi} \quad \delta_{\pi e} > 0 \qquad (3)$$

Where $\Delta\pi_t$ = actual inflation (measured by the annual percentage change in the consumer price index)

$\Delta\pi_t^e$= expected inflation (calculated as the percentage change in the forecasts of the consumer price index of each samples' frequency)

The presence of a cointegrating relationship between the two, given that they are both non-stationary and integrated of the same order, is evidence of a stationary error process. Once the VAR was estimated, the Johansen (1988) method is used to test the null hypothesis of no cointegration. They chose the Johansen method over that of Engle-Granger (1987) because of its relaxed nature regarding specification sensitivity. Additionally, they reject the Engle-Granger approach because of the potential for invalid hypothesis tests that may result from non-standard distribution of the OLS standard errors in the cointegration regression. Johansen trace statistics confirm the existence of *weak* rationality with a failure to reject the null hypothesis of no cointegrating relationships at a 10% level of significance. As they point out, only one other study besides theirs, that of Paquet (1992), was found to use

evidence of cointegration as a test of RE. By applying a different empirical test for RE, their work represents a new perspective on the four-decade-old REH debate, and for this reason alone merits further exploration.

Additional Contributions of the Study

This study incorporates an innovative approach to the examination of rational expectations by examining forecasts in a VAR model using quarterly forecasts from both the Livingston Survey and ASA-NBER SPF. This is done to uncover the short-run dynamics of the forecast error process and examining the nature of the apparent forecast inefficiencies uncovered by Shuh (2001) and Croushore (1998). Before the VAR is constructed, however, single equation OLS regressions for the classic test of rational expectations (specified in equation (1)) are estimated using quarterly data for the same variables tested at the annual level in Shuh (2001)[14] plus additional variables that may have explanatory power over the forecast errors. The additional variables included are a measure of the money supply (M1), the output gap, the relative price of energy, long term interest rates (10 year Treasury bond), the yield spread between short (3-month T-bill) and long term (10-year T-bond) interest rates. Addition of these variables constitutes an expansion of the subset of public information available to the forecaster, and statistically significant coefficients indicate inefficient use of information pertaining to the variables. Using the single-equation method to test RE ensures that similar inefficiencies exist quarterly as those found separately by Shuh and Croushore in annual data, and it also averts over-specification of the VAR by identifying those variables exhibiting some significant degree of inefficiency.

[14] Shuh (2001) examines output (real GDP), unemployment, interest rates, and forecasts thereof as contained in the ASA-NBER Survey of Professional Forecasters.

This study also recognizes the advantages of using a VAR approach to testing rational expectations like the work of Grant and Thomas. However, rather than focusing on the cointegrating relationship between inflation and expected inflation, a multivariate specification is used to introduce a subset of all information variables and analyze the effects that these other endogenous variables have on forecast errors. This is done primarily because the evidence of weak form rationality in the results of Grant and Thomas (1999) begs the question of what dynamics exist in the economy that explain the behavior of forecast errors, given the long-run cointegrating relationship between inflation and its expectations. Indeed, the approach used in this study may lend credence to their findings by explaining some of the variance in the residual term that most likely led to an observation of weak rationality.

CHAPTER III

METHODOLOGY

Data Descriptions and Sample Period

This study examines inflation forecasts and subsequent forecast errors contained in the Livingston Survey and ASA/NBER SPF using semi-annual data in the former and quarterly data in the latter. The data sets are constructed from non-overlapping forecasts for the period from 1960 and 1969, respectively. For a complete description of the survey data sets and all variables used see Appendix A.

Certain considerations were necessary to convert the data from the Livingston Survey into usable, non-overlapping intervals.[15] The survey is distributed semi-annually in the months of May and November with current data as of April and October asking respondents for a CPI forecast for December and next calendar year June. This convention equates to 8 and 14-month forecasts of the CPI and must be converted to a semi-annual rate of inflation to be used in this study. The longer-term (14-month) forecasts are ignored to avoid the issues of overlap and revision presented in Keane and Runkle (1990) so that the end result is a June and December forecast of inflation. By restricting the forecast window to 6–month increments, the analysis should represent the forecasters' true *near-term* expectations of inflation, which seems intuitively reasonable, given that the focus is to examine *short-run* inefficiencies and error behavior. The SPF follows a more natural convention in that one-quarter-ahead forecasts are solicited on a quarterly basis.[16] This important difference in survey frequency should be noted to avoid misinterpretation of side-by-side comparisons

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[15] A complete explanation of the data conventions contained in the Livingston Survey including all documentation is available on the world wide web at http://www.phil.frb.org\econ\liv\index.html

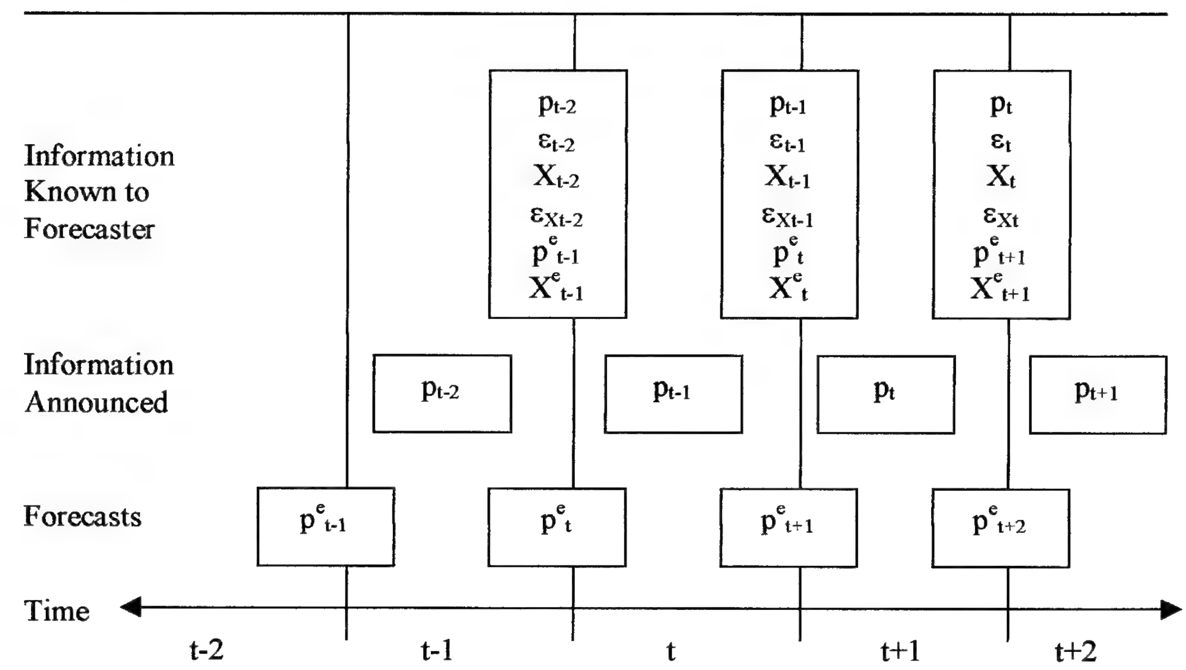
[16] Croushore (1993) contains complete details of the survey or they can be found on the world wide web at http://www.phil.frb.org\econ\spf\index.html

presented later in the results section.

Actual data used in the analysis were obtained from the Federal Reserve Bank of St. Louis "*FRED*" database.[17] Quarterly (and semi-annual) variables were derived from monthly data so that the conventions of the survey correspond as closely as possible to an exact date of measurement rather than an average value.[18]

As pointed out in Keane and Runkle (1990), it is imperative that the set of information used to test RE represents the true information set *available to forecasters at the time of their forecast*. Figure 1 below summarizes the assumptions of data availability for each successive inflation forecast.

Figure 1. Forecast Information Availability



The top portion of this figure shows what information is considered known by the forecaster

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[17] All FRED series are available on the world wide web at http://www.stls.frb.org/fred/

[18] For example, end of month March data is used as a first quarter data point, end of month June a second quarter data point, etc., so each is a true *point estimate* for the end of a given quarter.

at the time of forecast. This issue of what is considered *known* or *unknown* to forecasters is not relevant to the tests of bias, but very important to the tests of efficiency. If a forecaster could not possibly have known a specific piece of information at the time of his forecast, it is impossible to efficient use of that information. Notice that at each point in time that a forecast is made, only t-2 or further lagged data regarding the information variables is available to the forecaster. This is an important concept because incorrect assumptions about the availability of information lead to invalid tests of rationality.

Global Model Assumptions

Specific model assumptions are detailed in the sub-sections of this chapter that follow for the single-equation regression and unrestricted VAR, but there are two important global assumptions applicable to all model specifications. These were alluded to in Chapter 1 in describing the problems with the simple regression equation model and require further clarification now.

The first involves the use of aggregate survey data as opposed to individual forecast data. As detailed in Keane and Runkle (1990), using OLS with aggregate data assumes errors are uncorrelated across the sample of forecasters for any given point in time, which they show to be incorrect. Making this assumption and using the OLS method "suggests there is less uncertainty than there actually is about the regression coefficients". [19]

To account for this problem they develop an alternative method (Generalized Mean of Moments (GMM) using panel data regressions) to take into account this correlation. Shuh (2001) counters the arguments made by Keane and Runkle (1990) rather effectively in his defense of OLS, and it would be easiest and probably wisest to hide behind the shield of

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[19] For a complete discussion of this topic, refer to Keane and Runkle (1990).

valid points he puts forward.[20] However, it is not clear that it is necessary. Recall that this study's bivariate regressions are a tool to identify macroeconomic variables that exhibit potential inefficiencies associated with the forecasts of inflation. Information variables with relatively high p-values in the test for efficiency are excluded from further consideration in the VAR specification. This bivariate test is done primarily to avoid over-specification of the VAR, not to refute or support RE. This approach does not remedy the problem, and the results are *still* subject to the same criticisms of aggregation bias and possible model mis-specification. Therefore, the significance of parameter estimates in these bivariate models should be interpreted with caution, however, it is not deemed a fatal error to use average or consensus data in this manner to identify tendencies of inefficient information usage. The bivariate regressions also provide a check of robustness for Shuh's (2001) annual results using quarterly data.

The second issue concerns lack of information regarding the set of privately available information and the potential impact on the results. This problem is not considered a pervasive problem with the Livingston Survey data because the majority of data points are from *non-professional* forecasters. It could potentially be a problem with SPF, however, and the issue is certainly not as clear-cut as that of aggregation bias. Of course, any variance of the forecast errors explained by private information about the subset of public information variables is captured in the coefficients of the public information vector, but separating the two is not possible. Such private information is certainly not published and cannot be accounted for in this study, given the use of aggregate data. Even *if* the data were not

[20] Shuh (2001) cites specific problems with the panel regression including lack of performance variance across forecasters, unbalanced panels, and shortcomings of GMM in small samples.

aggregated, without knowledge of all individual forecast model details, it is not possible to correctly specify a model that allows the intercept and expectations coefficient to vary for each separate forecaster. Fortunately, the only case where private information effects would entirely invalidate the inferences made in this study occurs if inefficient use of private information dominates that of public. This is highly unlikely, and therefore, a simplifying assumption is made that forecasters use any private information efficiently. To explain the logic of this assumption, consider a simple analogy where the trainer of a basketball team knows details of the team's health that could affect the team's performance, but they are not made public for strategic purposes. Isn't the trainer more likely to accurately predict the outcome of a game having this information as compared to a someone without this knowledge? The answer, of course, is yes. Similarly, it is not logical to expect private information about prices to be used *inefficiently*, and the inferences of the study should be valid despite the exclusion of all *private* information.

Single Equation RE Testing

The methodology used in the single bivariate equations is similar to that used in Shuh (2001) to test for bias and efficiency. The only difference is that with the use of quarterly data, additional AR terms must be added to correct for serial correlation of the errors. It should also be noted that the forecast errors exhibit a non-constant variance such that standard errors must be modified by White's heteroskedasticity-consistent covariance matrix estimator to produce valid hypothesis test results. This correction, of course, diminishes the power of the efficiency test.

In addition to Shuh's methodology, which includes inflation expectations and one of the information variables as regressors in the specification, the following single-equation

regression model was estimated for each information variable. The equation mirrors the original specification of Mullineux (1978) to test the REH:

$$(p_{t+1} - {}_t p_{t+1}^{e} =)\ \varepsilon_{t+1} = \beta_0 + \beta_2 X_{t-1} + \varepsilon_t \qquad (4)$$

Notice that this specification does not include forecasted prices in the right hand side variables; hence, there is an implicit one-to-one correspondence between actual inflation and expected inflation. This undermines the strength of the test for rationality as compared to equation (1), but, again, that is not the focus of this exercise.[21] Additionally, the percent of the variation explained by the information variable calculated as the individual adjusted $\overline{R}^2$ is a valuable by-product of using this transformation and provides a crude rank ordering of the variables in terms of potential inefficiencies.

Multivariate Unrestricted VAR

Once the information variables were tested for efficiency using the single-equation process described above, the reduced form VAR was constructed. A short explanation of what composes a vector autoregression or VAR model follows for those unfamiliar with this type of regression.

What is a VAR and why use it in this study? A VAR or vector autoregression model in its unrestricted form expresses each endogenous variable as a function of its own lags, lags of all other endogenous variables, and a serially uncorrelated error term. VARs are commonly used for forecasting systems of interrelated time series, but the ability to analyze the dynamics of a system of equations is most important to this study. By assessing the impact of random shocks on the system of variables, it is possible to make inferences about events in the economy that cause forecasters to deviate from RE in the short run. OLS is appropriate

[21] The assumption that β_1=1 is a restriction that , if wrong, invalidates the hypothesis test results.

because with only lagged values of the endogenous variables on the right-hand side of each equation simultaneity is a non-issue.

The following is the mathematical representation of an unrestricted VAR: .

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \beta x_t + \varepsilon_t \quad (5)$$

where y_t = k vector of the endogenous variables,
x_t = d vector of exogenous variables,
A_1 - A_p and β are matrices of coefficients to be estimated
ε_t = vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

Specification of the VAR in this study is based on Sims' (1980) methodology that entails a simple determination of the appropriate variables to include in the VAR, based on a relevant economic model, and an appropriate lag length test.[22] In this case, as long as the endogenous variables have a causal macroeconomic link to inflation or expected inflation, it is valid to include them in the public information vector. Any variables considered must be tested for the existence of a unit root prior to inclusion in the VAR. If one exists and the process is I(1), first differencing is necessary to ensure all series in the VAR are stationary. This goes against the opinions of Sims (1980) and Doan (1992). Both advise "against differencing even if the variables contain a unit root because it 'throws' away information concerning the co-movements in the data (such as the possibility of cointegrating relationships)".[23] However, it is more important here that the VAR represent the true data-generating process, hence the use of differencing to ensure stationarity. Using stationary transformations of the data also leaves the option open to create a structural VAR by imposing coefficient restrictions on the reduced form VAR or a vector error correction

[22] Enders (1995), page 301.
[23] Enders (1995), page 302.

representation. Each series was tested for existence of a unit root using a Phillips-Peron test and differenced when necessary to ensure stationarity.

The next step was to select the appropriate lag length. This was done comparing the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) calculated by the following equations respectively:

$$AIC = -2£/T + 2k/T \tag{6}$$
$$SC = -2£/T + (k\log T/)/T \tag{7}$$

Where £ = log likelihood
T = number of observations
k = number of estimated coefficients

The trade-off between the two is that of parsimony and fit with the SC favoring the more *compact* model by penalizing for the inclusion of additional lags. The latter is preferred to the former for our purposes, because inflation and its expectations are affected by changes in the economy with a considerable lag. The omission of important lagged information is unacceptable, particularly with regard to the IRF analysis and variance decomposition.

Once the lag length is selected, the unrestricted VAR is estimated with OLS for each of the two survey data sets. Because of the method used to specify the model, any coefficients found to be significantly different from zero represent inefficiency within the forecasts of inflation. The unrestricted VAR is then estimated and analyzed using different sample selections, combinations of variables, sensitivity analysis, and a battery of diagnostic tests to verify the validity of the model and understand any changes in the dynamics over the course of the entire sample period.

Two valuable by-products are then created from the estimation results to analyze the dynamics of the model: the impulse response functions and the variance decompositions. They are the keys to understanding how changes in the economy affect inflation and expectations of inflation differently.

CHAPTER IV

RESULTS OF THE STUDY

Structure of the Results

This chapter is divided into three sub-sections. The first part presents the descriptive statistics of the data and time series plots of actual inflation compared to expected inflation, as well as the forecast error plots derived from differencing the two. A solid understanding of the time trend of inflation in the sample and the associated forecast errors will make the second and third sections of this chapter easier to interpret. The second section presents an analysis of the single-equation regression results in a context similar to that presented by Shuh (2001), with the exceptions noted in the previous chapter. The third and final part of the results examines forecast errors in the multivariate vector autoregression (VAR) model, including an impulse response function analysis and variance decomposition of forecast errors.

Forecast Error Descriptive Statistics and Time Trends

The first place to start when examining the history of inflation forecast errors is the average, or mean, of the errors. Going back to the meteorologist example, good forecasts are expected to be correct on average over time. Any prolonged one-sided errors would be evident from a simple calculation of the mean of the errors over the sample period. Referring to Table 1, data for the full sample period in both the Livingston and SPF Surveys exhibit weak evidence of bias. Note that all three means are significantly different from zero over the full sample. However, when the sample is split at the end of 1982 and the two sub-sample means are calculated, it is apparent that any evidence of bias occurs before the break. The end of 1982 as a break point is a natural choice for two reasons. First, it keeps the high

Table 1. Forecast Error Descriptive Statistics

Variable	1960 – 2000		1969 – 1982		1983 – 2000	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
MEDIAN LIV ε^{π}	.34**	1.03	.82**	1.43	-.06	.66
N	81		28		35	
	1969 – 2001		1969 – 1982		1983 – 2001	
MEDIAN SPF ε^{π}	.18**	.60	.38**	.75	.03	.38
MEAN SPF ε^{π}	.17**	.58	.37**	.74	.02	.36
N	129		56		73	

* indicates that the mean is significantly different from zero at the 10 percent level
** indicates that the mean is significantly different from zero at the 5 percent level
Sources: Livingston Biannual data from 1960 - 2000
ASA/NBER Survey of Professional Forecasters 1969 - 2001

inflation, high volatility of the 1970's on one side of the sample. Second, the period known as the Volcker deflation began in 1979 and continued until the end of 1983, during which inflation was substantially reduced under an aggressive, anti-inflationary monetary policy pursued by the Federal Reserve.[24] A specific date cannot be cited, but it is generally viewed that the conduct of monetary policy changed to an approach of using interest rates to target an optimal rate of growth and inflation early in Chairman Volcker's tenure, a policy that has continued under the leadership of Chairman Greenspan.[25] Although it is too early to draw any conclusions, the mean hypothesis test of forecast errors implies that perhaps the change in policy conduct made it a bit easier to predict the direction and magnitude of future prices. This theory is revisited later in this chapter.

[24] Appendix C contains the results of a Chow Breakpoint Test and recursive coefficient analysis, which both confirm the existence of a structural break at the end of 1982 in both surveys.
[25] Judd and Rudebusch (1998), page 4.

Next, a look at the history of inflation compared to expected inflation within the two surveys puts the problem addressed in this study into context. Figures 2 and 3 plot the two series for the samples analyzed in this study. The SPF Survey sample contains data back to 1969, and the Livingston Survey to 1960.[26] Notice that the graphs have been shaded to show the split in apparent bias mentioned above.

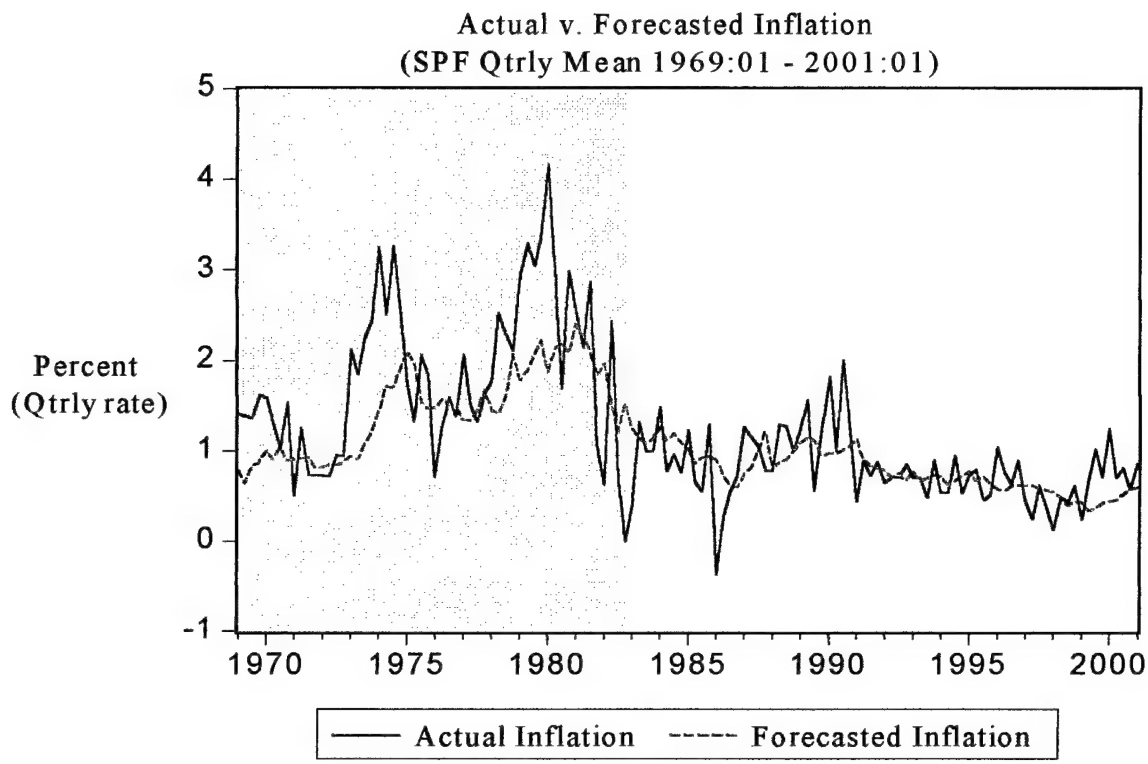
The graphs show that despite this earlier weak evidence of bias, both forecasts exhibit traits that would be expected of good forecasts. Both generally track inflation rather well and are less volatile than actuals. Note that the two relative volatilities cannot be compared directly due to the sample frequency difference. Recall that the SPF has a quarterly frequency and the Livingston a semi-annual, so the additional *"noise"* of the SPF forecast is to be expected. This frequency difference also makes the *absolute* values incomparable unless you double the SPF or halve the Livingston.

The SPF plot shows that forecasters consistently under-predicted inflation for most of the 1970's except for a couple non-consecutive quarters in 1974 and 1975. Also notable is that the forecasters generally lag the turning points of actual inflation by a quarter throughout the entire sample. It is obvious why the mean hypothesis test shows bias in the first sub-sample where large forecast errors resulted from the oil price shocks of the 1970's. Forecasters do a much better job of predicting inflation in the second sub-sample, especially during the first half of the 1990's, when the quarterly rate of inflation was less volatile. This pattern of low errors continues until the third quarter of 1998 when inflation more than doubled from a 2% annual value to 4%. Notice how the two series diverge from the third quarter of 1998 until the third quarter of 2000, and then compare this anomaly to the rest of

[26] The Livingston Survey actually contains data back to 1947 but the scope of this study was initially limited to 1960 based on the availability of some *actual* variables, then restricted further to 1969 for purposes of comparison with the SPF.

the sample. The only period with as many consecutive one-sided errors occurs during the

Figure 2. SPF Actual and Forecasted Inflation

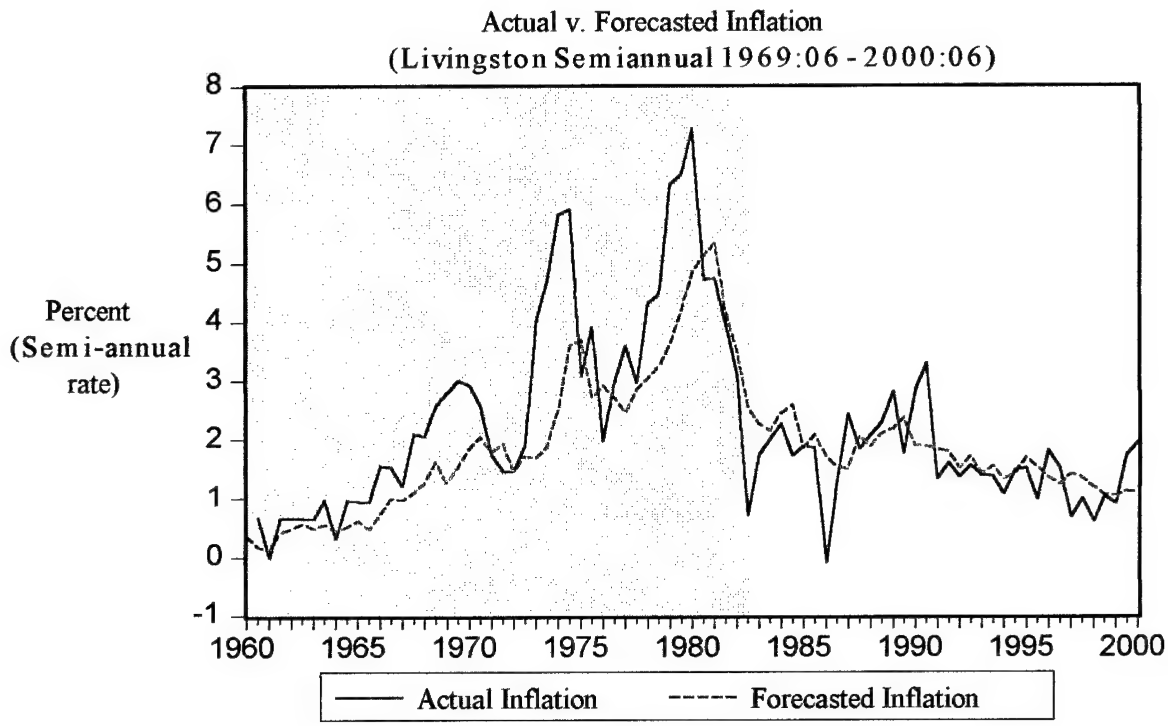


mid-1970's and the double-digit annual inflation of the late 1970's and early 1980's. Granted, the recent divergence is not as pronounced as that experienced in the 1970's, but it still shows some degree of abnormality, compared with the rest of the data set.

Similarly, the Livingston plot shows that *non-professional* forecasters, as respondents of this survey group are sometimes characterized in the literature, also under-predicted inflation for most of the first sub-sample. Although the graph gives the impression that these forecasters did a better job of reacting to the high inflation of the 1970's, this is not the case. Remember, the length of the sample is longer and the frequency is biannual. If we calculate the mean of forecast error again using the same sample period as the SPF and normalize the

Livingston data to a quarterly rate, the mean of forecast error is .45 for the Livingston compared to .37 for the SPF.

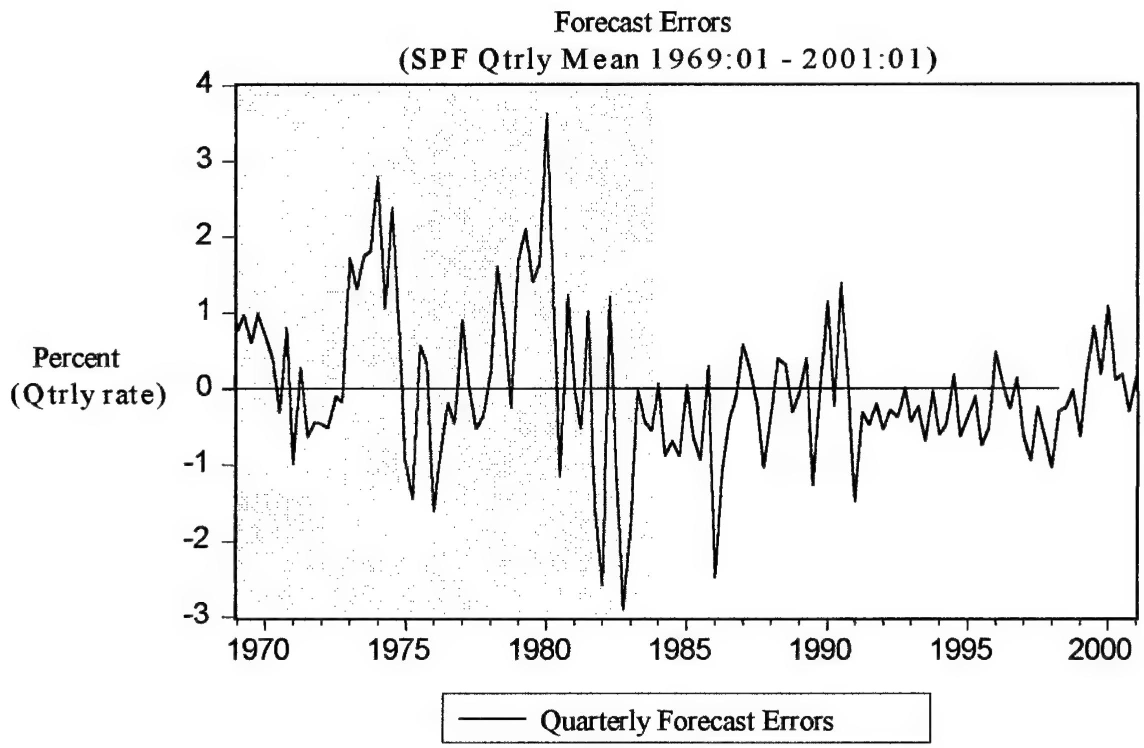
Figure 3. Livingston Actual and Forecasted Inflation



Probably the most surprising difference in the plots is the lack of a *prolonged*, recent divergence between the two series of the Livingston graph. However, this anomaly is explainable as well. Notice that the Livingston forecasters were over-predicting inflation for the three semiannual periods before 1998, and that there is one less year of data available for the Livingston survey. Together, these two facts tend to hide the divergence, which extends beyond the sample period shown. Other than these noted differences, the two forecasts behave similarly over the entire sample.

It is easier to get a better idea of the relative *quality* of the two forecasts by analyzing plots of the forecast errors themselves. The convention for calculating the forecast errors follows examples in previous literature such that forecast errors are equal to actual minus expected inflation. Therefore, any positive values represent under-predictions and negative values the opposite. Figures 4 and 5 show these plots.

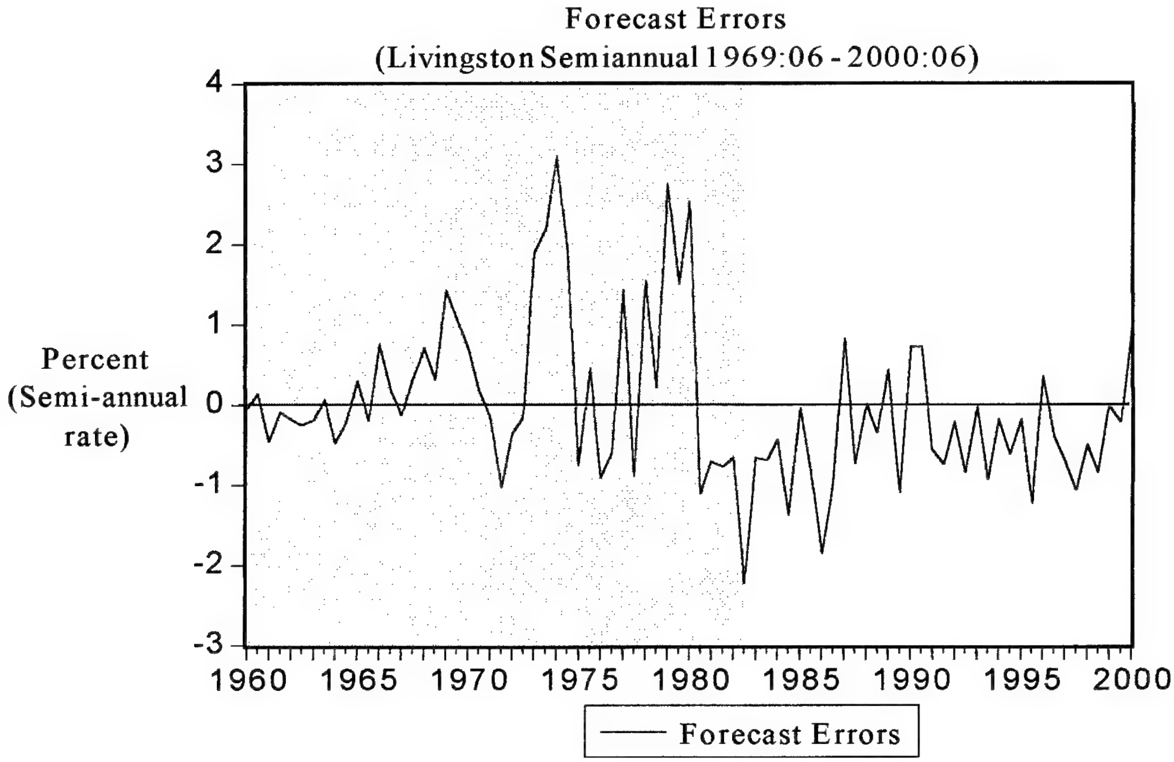
Figure 4. SPF Quarterly Inflation Forecast Errors



The SPF forecast errors are less one-sided and, for the most part, centered on zero. In contrast, the Livingston forecast errors appear one-sided in both sub-samples, not as significantly in the first, but enough so that neither is centered on zero. Both are much more volatile before the proposed structural break in 1983. Comparing the surveys on these plots alone is rather difficult given the differences in frequency and sample length, but the stronger

bias and higher volatility of the Livingston survey data indicate that the SPF may be the more accurate of the two. The last important note is the non-constant variance of the two series.

Figure 5. Livingston Semi-annual Inflation Forecast Errors



Recall that one of the tenets of RE is that the forecast errors exhibit a constant variance. Each of these series appears to be heteroskedastic in nature. This is an important issue for tests of efficiency because OLS produces biased standard errors in the presence of heteroskedasticity and must be corrected to ensure valid hypothesis testing.

Single Equation Test of Bias

As pointed out in the previous chapter, testing for bias of a forecast involves regressing the actual against the forecast value and a constant, then testing the joint coefficient restriction: H_0 $[\beta_0\ \beta_1]=[0,\ 1]$. Table 2 presents the results of this test.

Table 2. Regression Tests for Bias

Variable	Sample	β_0	β_1	R^2	p-value
	1969 – 2001	.45	.67**	.64	.11
π_{SPF}	1969 – 1982	.82*	.70**	.59	**.00**
	1983 – 2001	.36*	.59**	.29	**.05**
	1960 – 2001	.44	.96**	.67	**.03**
π_{LIV}	1960 – 1982	.99	.79**	.74	.27
	1983 – 2001	.37*	.74**	.23	**.02**

* indicates that the coefficient is significant at the 10 percent level or higher
** indicates that the coefficient is significant at the 5 percent level or higher
Bold indicates the test for unbiasedness: H_0: $[\beta_0\,\beta_1] = [\,0\ 1]$ is rejected at the 10 percent level or better with an F-test. All models have been corrected for serial correlation of the errors and use White's HC Cov to compute SE of the coefficients.

The results indicate significant bias over the entire sample for the Livingston Survey, but not so for the SPF. These results support the inferences made from the plots of the data. The quarterly and semiannual forecasts of inflation, unlike Shuh's (2001) test of annual data in the SPF, exhibit some significant bias. The next step is to test the joint hypothesis of unbiasedness *and* efficiency.

Single Equation Joint Test of Bias and Inefficiency

A similar methodology is used to test jointly for bias and inefficiency. Each of the information variables is added to the right hand side of the regression equation from the test for bias alone. Then the model is corrected for any serial correlation of the errors. Finally, to ensure robust standard errors in the presence of unknown heteroskedasticity, White's heteroskedasticity-consistent covariance is applied to correct the time dependent variance of the forecast errors noted in the data plots.

The results are split into two tables based on whether or not the forecaster had knowledge of the variable when making the forecast. Recall the discussion of what a forecaster can and cannot be expected to know when making a given forecast, as depicted in Figure 1 of Chapter III. Table 3 contains variables that the forecaster could not possibly have known, and hence, any inferences about efficiency based on the tests would be nonsense. Despite the irrelevance of these *unknown* variables in terms of testing efficiency, the regressions are still important for the information that they provide about explaining forecast error variance. Conversely, the variables in Table 4 are expected knowns and inferences regarding bias and efficiency are valid.

The tables are organized in the following manner. Each line of the tables represents a separate regression with the column denoted X_t showing the explanatory regressor in each equation. A superscript "*e*" means that the variable was a forecast, and the subscript denotes the relation in time to the inflation forecast. The estimated coefficients are shown with t-statistics in parentheses and the p-value refers to the probability of a joint F-test where the null is $H_0[\beta_0, \beta_1, \beta_2] = [0, 1, 0]$. The results are predictable in that the null is rejected in almost all cases of the variables not known to the forecasters. This passes the logic test.

Information that is not available at the time of the forecast is not expected to be used efficiently. The two exceptions where the null is not rejected, consensus *forecasts* of output

Table 3. Regression Tests for Inefficiency – SPF Unknown Variables

X_t Variable	β_0	β_1	β_2	p-val	R^2	Reject H_0
Δy^e_t	.36 (.45)	.74** (.37)	.08 (.19)	.55	.65	No
Δu^e_t	.50 (.45)	.65* (.38)	-.22** (.16)	.23	.64	No
Δi^e_t	.33 (.13)	.63** (.17)	.26** (.07)	**.01**	.26	Yes
Δy_{t-1}	.26 (.24)	.85** (.21)	.09* (.05)	**.05**	.67	Yes
π_{t-1}	.04 (.10)	.60** (.16)	.44** (.12)	**.00**	.67	Yes
Δu_{t-1}	.28 (.24)	.88** (.21)	-.41** (.07)	**.00**	.69	Yes
Δi_{t-1}	.21 (.18)	.94** (.17)	.11** (.03)	**.00**	.70	Yes
g_{t-1}	-.09 (.07)	1.34** (.27)	.30** (.05)	**.00**	.69	Yes
s_{t-1}	.50** (.16)	.95** (.13)	.20** (.04)	**.00**	.71	Yes
Δm_{t-1}	.27 (.23)	.79** (.19)	08 (.03)	**.01**	.68	Yes

Note: Standard errors in parentheses.
* indicates that the coefficient is significant at the 10 percent level
** indicates that the coefficient is significant at the 5 percent level
Bold indicates the joint test of unbiasedness and efficiency:
H_0: $[\beta_0\, \beta_1\, \beta_2] = [0\ 1\ 0]$ is rejected at the 10 percent level or better. Models may contain AR,MA, or both terms to correct for serial correlation of the error terms.
Variables are GDP Growth (y), Money growth (m), Unemployment (u), 3-Month T-billl (i), Output Gap (g), and yield spread between short and long term interest rates (s)

and unemployment, were probably mistakenly treated as unknowns. It is plausible that forecasters would have knowledge of the forecasts for other macroeconomic variables solicited in the survey, albeit only their own values, not the consensus forecast values.

When the explanatory variables are lagged by 2 quarters, they are expected to be known and utilized by an efficient forecaster. The same regression models used above are estimated again replacing the t-1 with t-2 data. Table 4 that follows shows these regression results and the subsequent Wald (F distribution) test of coefficient significance.

Table 4. Regression Tests for Inefficiency – SPF Known Variables

X_t Variable	β_0	β_1	β_2	p-val	R^2	Reject H_0
Δy_{t-2}	.36 (.24)	.84** (.22)	-.05* (.06)	.28	.67	No
π_{t-2}	.30 (.23)	.81** (.27)	.04 (.14)	.34	.66	No
Δu_{t-2}	.34 (.25)	.84** (.22)	.02 (.07)	.33	.67	No
Δi_{t-2}	.37 (.27)	.81** (.23)	-.02 (.03)	.19	.67	No
g_{t-2}	.35 (.27)	.83** (.23)	-.08** (.15)	.33	.67	No
s_{t-2}	.36* (.19)	.93** (.15)	-.08 (.06)	**.10**	.67	Yes
Δm_{t-2}	.35 (.25)	.78** (.22)	04 (.04)	.28	.67	No

Note: Standard errors in parentheses.
* indicates that the coefficient is significant at the 10 percent level
** indicates that the coefficient is significant at the 5 percent level
Bold indicates the joint test of unbiasedness and efficiency:
H_0: $[\beta_0\ \beta_1\ \beta_2] = [0\ 1\ 0]$ is rejected at the 10 percent level or better. Models may contain AR, MA, or both terms to correct for serial correlation of the error terms.

The results are consistent with RE except for a marginal p-value on the spread between long and short-term interest rates (s_{t-2}). A rejection of the null indicates that the yield spread exhibits significant inefficiency. None of the estimated coefficients' p-values warrants exclusion per se from the VAR, but it is not likely that any of the variables will show

significant evidence of inefficiency unless it occurs with a lag greater than the two periods presented in Tables 3 and 4.[27]

The results for this joint test using the Livingston Survey data also supports *weak form* rational expectations of inflation. Refer to Table 5 results shown below.

Table 5. Regression Tests for Inefficiency – Livingston Unknown Variables

X_t Variable	β_0	β_1	β_2	p-val	R^2	Reject H_0
Δy^e_t	.09 (.79)	1.02** (.30)	.11 (.14)	.52	.67	No
$\Delta^2 u^e_t$	.57 (.46)	.89** (.23)	.17 (.22)	.30	.71	No
Δy_{t-1}	.53 (.47)	.90** (.22)	.01 (.08)	.30	.71	No
π_{t-1}	.77 (.79)	.96** (.29)	-.14 (.19)	.53	.71	No
$\Delta^2 u_{t-1}$	.53 (.45)	.90** (.23)	-.11 (.22)	.32	.71	No
$\Delta^2 i_{t-1}$	.57 (.47)	.89** (.24)	.01 (.06)	.36	.71	No
g_{t-1}	-.11 (.34)	1.23** (.17)	.53** (.11)	**.00**	.77	Yes
s_{t-1}	.69** (.17)	1.05** (.11)	-.32** (.10)	**.00**	.68	Yes
Δm_{t-1}	.41 (.46)	.86** (.25)	08* (.05)	.19	.72	No

Note: Standard errors in parentheses.
* indicates that the coefficient is significant at the 10 percent level
** indicates that the coefficient is significant at the 5 percent level
Bold indicates the joint test of unbiasedness and efficiency H_0: $[\beta_0\ \beta_1\ \beta_2] = [0\ 1\ 0]$ is rejected at the 10 percent level of significance or greater.
Models may contain AR, MA, or both terms to correct for serial correlation

[27] No specific criteria was established to exclude variables from the VAR based on their estimated coefficient significance. VAR candidate selection is a subjective assessment by the author based on the results of the Wald tests and the impact at the margin of variable coefficients.

In the case of the Livingston Survey, the forecasters receive strong signals of t-1 because data for half of the 6-month survey is included in the forecast solicitation sent to agents. This probably explains the infrequent rejection of the null for variables presumed to be unknown to forecasters. As was the case in the SPF, the yield spread output gap variable exhibit some degree of inefficiency. The rest of the variables have relatively high p-values except money growth, which was to be included in the VAR regardless, given its strong causal relation to inflation in theory. The *known* variable results in Table 6 are similar to the SPF t-2 results. Again, output gap and the yield spread coefficients are highly significant, but overall the results support *weak form* RE similar to the results of the SPF public information subset.

Table 6. Regression Tests of Efficiency – Livingston Known Variables

X_t Variable	β_0	β_1	β_2	p-val	R^2	Reject H_0
Δy_{t-2}	.14 (.49)	1.01** (.21)	.11 (.08)	.13	.72	No
π_{t-2}	.57 (.45)	.79** (.30)	.08 (.17)	.38	.71	No
$\Delta^2 u_{t-2}$	.47 (.43)	.94** (.21)	-.16 (.17)	.18	.71	No
$\Delta^2 i_{t-2}$	.51 (.43)	.92** (.22)	.04 (.04)	.14	.71	No
g_{t-2}	.27 (.43)	1.07** (.21)	.48** (.11)	**.00**	.75	Yes
s_{t-2}	.56** (.25)	1.06** (.15)	-.25 (.09)	**.00**	.65	Yes
Δm_{t-2}	.45 (.43)	.89** (.21)	.04 (.06)	.36	.71	No

Note: Standard errors in parentheses.
* indicates that the coefficient is significant at the 10 percent level
** indicates that the coefficient is significant at the 5 percent level
Bold indicates the joint test of unbiasedness and efficiency:
H_0: $[\beta_0\ \beta_1\ \beta_2] = [0\ 1\ 0]$ is rejected at the 10 percent level or better. Models may contain AR, MA, or both terms to correct for serial correlation of the error terms. All model results in Appendix A

To summarize, the results of these single equation tests of bias and efficiency exhibit very few instances of statistical significance to refute RE. Specifically, only the output gap and term structure of interest rates bivariate regressions resulted in significant estimated coefficients for information *known* to the forecaster. However, many of the variables considered in the tests affect inflation and, thereby, expectations of inflation with a longer lag than the two quarters (SPF) or one-year (Livingston) examined in the single-equation section. This is exactly why using a VAR framework is necessary to analyze the dynamics and structure of any effects that are considerably lagged.

Unit Root Testing and Lag Length Selection

Two exercises are necessary before estimating the unrestricted VAR: unit root testing and lag length selection. The former is important to avoid any potential spurious (meaningless) regression equations in the VAR, and the latter helps identify the structure of the VAR by comparing the trade-off between parsimony and the exclusion of valuable lagged effects of the endogenous variables.

There are two schools of thought regarding the use of stationary versus non-stationary series in a VAR. Sims (1980), a pioneer of VAR estimation, advises against the use of stationary series, but the primary series of concern and overall goal of the study dictate otherwise. The unrestricted VAR must contain only stationary series because the dependent variable series, forecast errors, is known to be stationary. Use of non-stationary series with a known stationary series in a regression model could lead to what is known as spurious regression as referred to by Granger and Newbold (1974). Characteristics of a spurious regression include a high R^2 and t-statistics that appear highly significant, but the regression is void of economic meaning or interpretability because the residuals of such a regression are themselves non-stationary. That is, errors never decay and cause a permanent deviation

away from the model. Any hypothesis tests conducted in the case of a spurious regression are invalid, because the assumptions of OLS under which the test statistics are constructed are violated. Particularly, the variance of the error is not constant, $E(\varepsilon_t) \neq 0$, and there exists a high degree of autocorrelation in the residuals. Table 7 details the test for the existence of a unit root using the Phillips-Perron (PP) method. Note that since most series are already

Table 7. Unit Root Tests

Variable	Test Regression Form	PP Test Statistic	MacKinnon 1% Crit Value
Y	intercept	-8.74	-3.48
π	intercept	-4.06	-3.48
U	trend and intercept	-2.61*	-4.03
I	intercept	-2.62*	-3.48
F	no intercept or trend	-7.75	-3.48
G	no intercept or trend	-2.82	-2.58
S	intercept	-3.98	-3.48
M	trend and intercept	-6.50	-4.03
O	no intercept or trend	-11.64	-2.58

* Denotes non-rejection of the null at the 1% level of significance

transformed into growth rates for ease of coefficient interpretation (log-level first differences), the null of a unit root is predictably rejected. The only two surprises are the unemployment rate and yield spread between long and short term interest rates that indicate differencing is necessary. For space considerations, only the quarterly PP tests of the SPF are shown. The results are the same using the biannual Livingston data. Refer to Appendix D for complete hypothesis tests.

The Akaike and Schwarz (AIC/SC) criteria are used to determine the appropriate lag length of the VAR. Recall that the SC criterion favors the most parsimonious specification by penalizing additional lags of the variables. Table 8 below presents the calculated values,

the lowest representing the preferred lag structure. Since we have a relatively large sample for the SPF survey, the AIC is preferred to the SC because the loss of additional degrees of freedom by including additional lags is acceptable, whereas omission of potentially important lagged effects on forecast errors is not. Conversely, degrees of freedom *are* a concern with the Livingston sample size, and parsimony is an important objective of model selection.

Table 8. Lag Length Selection

Survey	Lag Length	Akaike Information Criterion	Schwarz Criterion
SPF	1	14.68	15.95*
	2	14.45	16.85
	3	14.88	18.82
	4	**14.13***	**18.82**
	6	15.47	20.25
	8	16.61	26.03
Livingston	1	16.39	18.02*
	2	**15.97**	**18.83**
	3	15.70	19.78
	4	15.85	21.16
	6	15.04	22.79
	8	12.59*	22.80

* Denotes optimal lag structure based on criterion
Bold denotes the model specification selected

The Schwarz criterion recommends a model with 1 lag, but because it is known *apriori* that forecasters do not have t-1 information, the next lowest SC model (2 lags) is selected. Based on the different forecast intervals (quarterly versus semiannual), this also normalizes the lag structure in terms of time for an easier comparison between the two surveys' regression results.

Multivariate Reduced Form VAR

Selecting the variables to include in the unrestricted VAR is simple and somewhat mechanical. Theoretically, any variable that affects inflation could similarly effect inflation expectations such that they respond equally if forecasters use information efficiently. Of course, there may be differences in the lag structure of responses, particularly with the SPF, because of its higher frequency and any t-1 information signals coming from a private rather than public source. The initial estimation of both surveys including the same information variables over the same sample is shown in Table 9. Based on a subjective assessment of the bivariate regressions the following variables are included in the VAR: real GDP (y), M1 money (m), unemployment (u), the 3-month treasury bill rate (i), and the difference between the 3-month treasury bill rate and the 10-year treasury bond rate (s).[28] Only the results of the forecast error equation rather than the entire six-equation model are shown in this table due to space considerations. The VAR is estimated for each sample with and without expectations of inflation included as an exogenous variable showing how the difference in the specification affects testing coefficient restrictions. The insignificant change in coefficients reflects that the inflation expectation coefficient ($1-\beta_1$) is not significantly different from zero, as expected.[29] Also, note the SPF model has two rather than the AIC recommended four lags. This convention was adopted for ease of comparison with the Livingston model and because no significant coefficients occurred after the second lag in initial trials of the model. The full results with all six equations are in Appendix E.[30]

[28] Additional variations of the VAR were estimated including the relative price of energy as a variable, but despite their coefficient significance pre-1983, the impact on the other estimated coefficients and fit of the model was minimal. See Appendix C for these additional model results.
[29] Inflation expectations are treated as exogenous based on the results of a test for Granger causality.
[30] These results include a sensitivity analysis incorporating the relative price of energy into VAR. This variable is added due to the high volatility of inflation in the 1970's, which was a result of the oil price shocks in that decade.

Table 9. Unrestricted VAR Results

	Livingston 1969 -2000		SPF 1969 -2000	
X_t Variable	π_t^e Exogenous	Explicit 1:1	π_t^e Exogenous	Explicit 1:1
ε^{π}_{t-1}	0.21	0.18	0.16	0.17
	(0.12)	(0.12)	(0.10)	(0.10)
ε^{π}_{t-2}	**0.47****	**0.40****	**0.19****	0.16
	(0.14)	**(0.14)**	**(0.09)**	(0.09)
Δy_{t-1}	0.10	0.07	-0.04	-0.04
	(0.07)	(0.07)	(0.07)	(0.07)
Δy_{t-2}	0.07	0.06	-0.09	-0.09
	(0.07)	(0.07)	(0.06)	(0.06)
Δm_{t-1}	0.21	0.22	0.08	0.07
	(0.15)	(0.15)	(0.04)	(0.04)
Δm_{t-2}	**0.34****	**0.36****	0.01	0.00
	(0.15)	**(0.15)**	(0.04)	(0.04)
Δu_{t-1}	0.03	0.00	**-0.52****	**-0.55****
	(0.36)	(0.36)	**(0.18)**	**(0.18)**
Δu_{t-2}	0.14	0.10	0.03	0.02
	(0.33)	(0.33)	(0.18)	(0.18)
Δi_{t-1}	-0.13	-0.21	0.07	0.05
	(0.17)	(0.17)	(0.07)	(0.07)
Δi_{t-2}	-0.04	-0.09	-0.04	-0.04
	(0.11)	(0.11)	(0.05)	(0.05)
s_{t-1}	**-0.38***	**-0.44****	0.17	**0.18***
	(0.20)	**(0.20)**	(0.09)	**(0.09)**
s_{t-2}	-0.06	0.00	0.04	0.02
	(0.18)	(0.17)	(0.09)	(0.09)
β_0	0.02	-0.47	**0.53****	**0.42****
	(0.52)	(0.44)	**(0.16)**	**(0.12)**
π_t^e	-0.26	-----	-0.11	-----
	(0.15)		(0.11)	

Note: Standard errors in parentheses and t-statistics in brackets
* indicates that the coefficient is significant at the 10 percent level
** indicates that the coefficient is significant at the 5 percent level

Diagnostics of all four models show that each is an adequate specification in terms of stability based upon the inverse roots of the characteristic AR polynomial, all of which have modulus less than one and lie inside the unit circle. A serial correlation LM test shows a slight degree of serial correlation among the residuals, but this is not entirely unexpected and can be corrected in the calculation of the IRF and variance decomposition. The fit of each

version of the model, measured by adjusted R^2, are in the same range with the percent of dependent variable variation explained ranging between .40 and .42 for all models.

Because of the way the models are specified, any significant coefficients signal some degree of inefficiency on the part of forecasters, but only if the information was considered *known* at the time of the forecast. By this standard, the only evidence of inefficiency for both groups across the entire sample occurs with their use of past consensus forecast errors. Livingston forecasters also exhibit marginal inefficiency pertaining to the growth rate of the money supply at a one-year lag. In the case of variables not known at the time of forecast, marginally significant coefficients appear for the spread between long and short term interest rates, but the sign of the effect is ambiguous between the two groups of forecasters. Additionally, the SPF forecast errors are significantly correlated with the growth rate of unemployment one quarter prior to forecast. Overall, however, the reduced form VAR results support *weak form* RE across the vector of information variables.

Rather than test the significance of each coefficient individually, Granger's (1969) Pairwise Causality Test is conducted. This test uses the coefficients on each lag to determine if each endogenous variable can be treated as exogenous by computing the Wald statistic distributed Chi-squared for the joint significance of all other endogenous variables. The results of the pairwise Granger Causality Test with inflation forecast error of is the dependent variable are shown in Table 10 below.

Table 10. Granger Pairwise Causality Test

Variable	Chi Square	Df	p-value
SPF (1969- 2001)			
y	7.47	4	0.1129
m	9.40	4	**0.0518**
u	18.41	4	**0.0010**
i	6.45	4	0.1680
s	10.90	4	**0.0277**
All	73.05	20	**0.0000**
Livingston (1969- 2000)			
y	6.81	2	**0.0333**
m	5.56	2	**0.0619**
u	0.01	2	0.9960
i	1.76	2	0.4138
s	9.77	2	**0.0076**
All	31.01	10	0.0006

Bold denotes significant at the 10% level for a joint test of all lags.

Based on the respective p-values of the endogenous variables for each survey model, it is expected that the impulse response function analysis will show that shocks to each endogenous variable will cause a different impact to forecast errors in each survey. This appears especially evident in terms of the growth rates of unemployment and output. The inference is made based on the relative *strength* of endogeneity of these two variables in the respective models of forecast error. Note that these results were calculated based on the full sample. Moving the sample window forward to 1983, when the variance in forecast errors declines notably, all hypothesis of exogeniety cannot be rejected at even the 10% level. In fact, the results of the Livingston tests over this sub-sample indicate that the forecast errors are indeed a white noise process. The change in the forecast error structure within the sample period is explored further in the last two sections of this study.

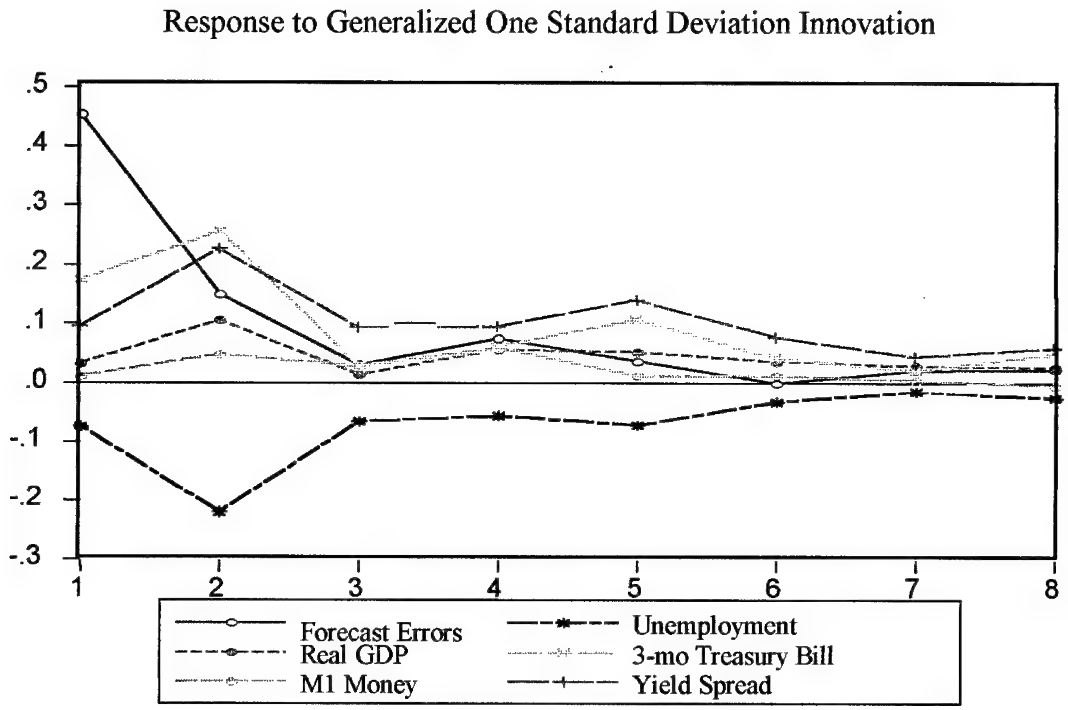
Impulse Response Function Analysis

Despite the favorable diagnostics showing the reduced form VAR models have stationary residuals, serial correlation among them may still pose a problem. If so, any impulse response function (IRF) analysis becomes impossible, because each innovation may have a common component that cannot be associated with a specific variable. Fortunately, the innovations can be transformed to remove correlation and orthoganalize the impulses so that they are interpretable.

There are two methods available to derive the IRF: the Cholesky method, which attributes effects based on the ordering of the variables in the VAR, and the method of generalized impulses, which does not depend on the ordering. Realizing that the ordering chosen with the Cholesky method can drastically change the impulse responses and there are 720 different combinations, this study uses the generalized method developed by Pesarin and Shin (1998). Figure 6 shows the response of the forecast error to a one standard deviation shock, or innovation, to the other endogenous variables.

The results indicate that innovations of past errors impact forecast errors the most. This is an expected result considering the coefficients calculated in the reduced form VAR and their corresponding significance. The same is true for the impact of innovations to the growth rate of unemployment. Innovations to output growth and money growth do not significantly impact the forecast error (refer to Appendix G for individual IRFs with standard error confidence interval bands). This stratifies the coefficient interpretation of the VAR in that forecasters use information regarding these two variables efficiently. This concept that the impulse responses of forecast

Figure 6. Impulse Response Function – Forecast Errors



errors are smaller in magnitude and decay more rapidly when forecasters are *more efficient* is explored using a recursive regression simulation later in this section. The IRFs generated over the full Livingston sample (not shown here) indicate no significant responses to innovations of any of the other endogenous variables and the IRF is nearly flat for all endogenous variables. (Refer to Appendix G). Does this imply that the Livingston forecasts of inflation are more efficient? Not necessarily, it is more likely that Livingston forecasters simply use last period's inflation more often as a proxy for next period's forecast so that any system dynamics driven by anything other than past forecast errors become immeasurable. This also may be a by-product of using semi-annual data points with the Livingston survey compared to the quarterly forecasts in the SPF. Shuh (2001) mentions the possibility of this

smoothing effect in comparing his study of annual data to past work with quarterly data.[31] Regardless, it renders the Livingston survey IRFs unusable for interpretation of system dynamics, because shocks to other variables appear to have zero effect on forecast errors.

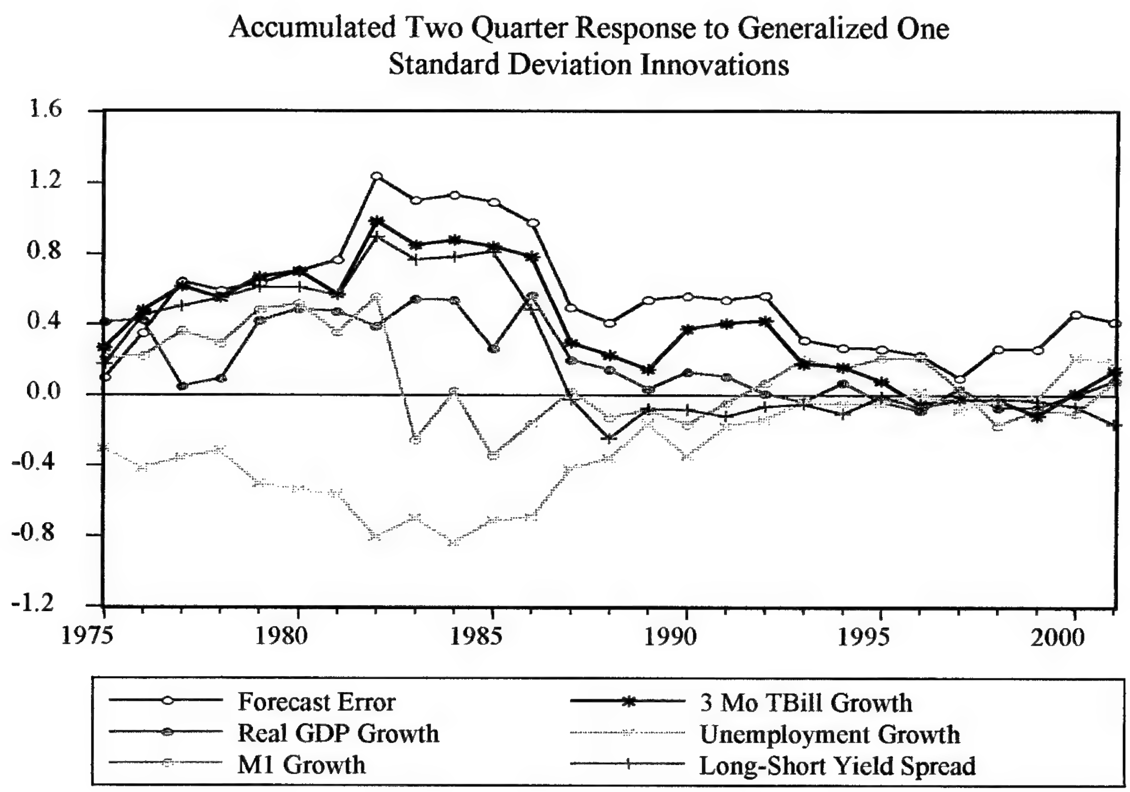
Returning to the concept of relating efficiency to impulse responses, a simulation was run to test whether there is a noticeable difference in the behavior of forecast error responses over the sample period. The idea is that when forecasts do not react efficiently to innovations of the other endogenous variables, the IRFs for the forecast errors will exhibit larger impacts and decay more slowly. For example, consider what happens when there is a shock to the growth rate of output. In the context of a simple money demand function, such a change is likely to increase the level of prices all else constant. If the shock translates into a significant increase in the forecast error of inflation, it means that actual inflation increased at a higher rate than expected. If the increase to inflation is more efficiently anticipated by the forecast, the response of the forecast error is smaller. In order to obtain this measure, the reduced form VAR for the SPF with two lags is used as a "*yardstick*" to calculate the two-period accumulated responses of the forecast error to a one standard deviation shock to each of the other endogenous variables. The estimation window is moved forward year by year using a six-year window of the sample, and the values of the impulse response are recalculated each time the sample range is changed.[32] Figure 7 below shows the graphical results of the six-year *sliding* model for the pseudo-recursive method described above. For example, data points presented for each variable for 1975 were calculated by estimating a reduced form VAR for the period 1969-1975. The second quarter following the shock was selected as the cut-off point for accumulated responses because most impulse responses

[31] Shuh 2001, page 39.

[32] Six years of quarterly data provides the minimum number of observations necessary to calculate the IRF with the SPF sample data.

either decay to zero at that point or are not significantly different from zero according to the standard errors.

Figure 7. Simulation of Sliding IRF Model



Note the relative magnitude of the impulse responses before 1983 (equates to 1989 in the figure above based on the six-year window convention) when the Fed began targeting interest rates to achieve stable growth and a desired level of inflation. From these results, it appears that the change in policy made it easier for forecasters to predict future inflation. This is evidenced, though not testable, by the diminishing impact that shocks to the other endogenous variables have on the forecast error of inflation. Did the change in the conduct of monetary policy change the way forecasters made forecasts, or is the anomaly driven by the oil price shocks of the 1970's? This question is probably best answered by a someone in

the business of forecasting in 1983, but this crude method of normalizing the magnitude of impulse responses certainly does nothing to dispel the idea that forecasting inflation has become markedly easier since the Fed changed its conduct of monetary policy. Testable implications of this hypothesis are left to future research.

Variance Decompositions

Another useful VAR analysis tool is the variance decomposition, which measures the relative effect that component shocks have on an endogenous variable. By calculating the variance decomposition of forecast errors, it is possible to determine if shocks or innovations to any of the other endogenous variables have a significant impact. Unlike the IRF, the variable ordering issue cannot be avoided for variance decompositions, meaning there are 720 possible ordering combinations. It would be too time consuming to perform a sensitivity analysis across all combinations, so some assumptions are made in accordance with the general guidelines of Cholesky ordering. These guidelines are summarized as follows:

1) If a variable is only affected with a lag, put it early in the ordering.
2) If it is influenced by all shocks all of the time, put it late in the ordering.
3) Financial variables should be placed late in the ordering.

Applying this criteria, forecast errors are placed first in ordering because they are always affected with a lag. The remaining ordering was selected based on the relative strength of endogeniety given by the pairwise Granger causality tests, and is as follows for the SPF: the yield spread growth, unemployment growth, money supply growth, the 3-month T-bill rate growth, and finally, real GDP growth. The same logic is applied to the Livingston survey model, resulting in the following Cholesky ordering—forecast errors, yield spread growth, GDP growth, M1 money supply growth, unemployment rate growth, and the change in the 3-month T-bill rate. The results are presented in Tables 11 and 12 below.

Table 11. SPF Forecast Error Variance Decomposition

Period	S.E.	ε^{π}	y	m	u	i	y
1	0.42	100.00	0.00	0.00	0.00	0.00	0.00
2	0.52	74.31	0.06	1.81	18.88	0.16	4.79
3	0.54	69.82	0.34	4.81	18.02	0.92	6.10
4	0.57	65.88	3.02	8.56	15.77	1.09	5.69
5	0.62	60.06	2.89	8.17	19.81	2.77	6.30
6	0.63	58.01	4.28	9.02	19.45	2.94	6.30
7	0.64	57.49	5.09	9.35	19.04	2.88	6.15
8	0.65	56.81	6.42	9.14	18.73	2.87	6.02
Cholesky Ordering: ε^{π} s y m u i							

Table 12. Livingston Forecast Error Variance Decomposition

Period	S.E.	ε^{π}	s	m	u	i	y
1	0.89	100.00	0.00	0.00	0.00	0.00	0.00
2	0.95	87.83	2.65	1.97	0.00	2.31	5.25
3	1.13	72.15	12.44	4.04	0.84	3.04	7.48
4	1.19	65.49	16.18	4.14	2.70	4.64	6.86
5	1.25	60.13	19.98	3.73	4.91	4.73	6.53
6	1.26	59.10	20.62	3.79	4.97	4.70	6.81
7	1.27	58.79	20.84	3.92	4.94	4.67	6.84
8	1.27	58.75	20.81	3.97	4.98	4.67	6.83
Cholesky Ordering: ε^{π} s y m u i							

The results are shown over two different horizons, given the frequency of the sample data. The SPF is shown for a two-year horizon, whereas the same eight periods equates to four years of Livingston survey data. Looking at the two across the *same* horizon (8 periods of the SPF equates to 4 periods of the Livingston), the results indicate that approximately 10% more of the variation in the SPF forecast errors is explained by the other endogenous variables. However, as with all other results up to this point, any comparisons between the two may be distorted by the smoothing effects of a lower survey frequency. Both indicate that growth and unemployment rates are the most important of the group in explaining error variance. A sensitivity analysis of these variance decompositions was done that included

both past inflation and past expected inflation in separate VAR models for each survey. Neither of which significantly affected the outcome of the decomposition. The results of additional trials of the modified VAR are available in Appendix H.

Overall, the fact that only 44% of the variation in the SPF forecast errors and 35% of the Livingston forecast errors are explained by the other variables after 2 years means that past forecast errors dominate all other variables combined. These results are consistent with earlier evidence of the single-equation efficiency tests that indicate efficient forecasts of inflation, and thereby, *weak form* RE, at the consensus level.

CHAPTER V

DISCUSSION, CONCLUSIONS, RECOMMENDATIONS

Summary and Interpretation of the Results

The preponderance of evidence in the single equation tests of bias and inefficiency and the VAR model tests of pairwise Granger causality support the formation of *weak form* rational expectations at the consensus or aggregate level. Using the VAR proved to be an excellent tool for examining borderline inefficiencies of forecasters identified in the single equation tests. In particular, the IRF analysis exposed a probable structural change in the way forecasts have been made beginning in the early 1980's, which, coincidentally, is about the same time the Fed moved toward an interest rate targeting agenda. The question remains as to whether this evidence of greater efficiency is a result of the policy change or just a quieting of forecast error variance after the oil price shocks and high inflation rates of the late 1970's and early 1980's.[33]

The reduced form VAR results for the SPF indicate that there are some potentially inefficient uses of information regarding past forecast errors at the consensus level, which is also true regarding the Livingston forecasters. However, these results are found only when estimating the SPF model over the entire sample. Any evidence of inefficiencies disappears when the same model is estimated for the period post-1983. Undoubtedly, this estimation problem is due, in part, to the heteroskedasticity detected in the quarterly forecast error data and the rapid decline in variance after the oil shocks of the 1970's. A similar result is shown

[33] Sensitivity analysis of the models with and without the relative price of energy indicate that the policy change seems more likely the cause, but formal tests are left to future research.

to be true in the Livingston data regarding the relationship between the growth rate of money and inflation forecast errors. The correlation is significant when the entire sample is considered, but not so after 1983. The slope of the yield curve, measured as the difference between the 3-month Treasury bill rate and the 10-year Treasury bond rate, is also marginally significant in explaining forecast errors of inflation, particularly in the Livingston data. This could be interpreted as a failure of forecasters' models to adequately capture the effects that a change to interest rates has on future inflation. More specific inferences regarding the yield curve coefficient is difficult because of the sign ambiguity between the two survey samples and the fact that it is not known whether the inefficiency is related to a change in short-term or long-term interest rates. This finding of marginal inefficiency as it relates to the term structure of interest rates concurs with the earlier work of Anderson (1997).[34]

Despite a conscious attempt by this study to avoid a *direct* test of rational expectations, the results provide no evidence to refute the hypothesis either. Neither the quarterly forecasts of the SPF, nor the semiannual forecasts of the Livingston Survey show statistically significant signs of inefficiency in the use of publicly available information. Therefore, the first initial hypothesis presented in the introduction is rejected. The second hypothesis leaves more room for an open interpretation of the results. The study has revealed marginally significant impacts of innovations to other variables on the forecast errors of inflation, but these effects are sensitive to the sample period selected such that any inferences of forecast error behavior may be suspect. The IRF analysis indicates a change in the relative efficiency with which public information is used to derive forecasts of inflation, but these indications are not testable in the framework of this study. The third hypothesis cannot be rejected based on the material presented. Past forecast errors seem to be the

[34] Anderson (1997), page 45.

strongest predictor of future forecast errors. This may be true in part because of the long-run anchors that exist in forecasters' models, or it may simply be the fact that forecasters avoid drastic changes to their predictions over successive periods. There is most likely a reluctance to concede past forecast errors, let alone model them to improve future forecasts. Recall, however, that the survey data is used in aggregate and the significance of past forecast errors as an explanatory variable might not exist at the individual level. Although this result is not likely, it *cannot* be ruled out given the detailed analysis using panel data in literature such as that of Cohen and Bonham (1998) or Keane and Runkle (1990).

Discussion of Policy Implications

Since the focus of this study was a decomposition of inflation forecast errors to identify those variables that tend to explain their variance; it is difficult to infer any policy implications considering the lack of evidence for inefficient forecasts. The results regarding interest rates do provide some useful information, albeit questionably significant, regarding policy. Assuming that a secondary monetary policy objective is to minimize the deviation of expected inflation from the Fed's target (i.e., minimize inflation forecast error), then the results imply that a stable rate of interest rate growth (or contraction) is less likely to distance the expected inflation rate from actual. This is important, especially if the presumption is that inflation trends more often than not *live up to expectations,* or more succinctly, that market price setters rely on accurate forecasts. If this is true, then it behooves the Fed to adjust interest rate targets slowly and deliberately, so as not to fool forecasters and consequently, price setters. A final analogy may strengthen this last point. If a pilot of a commercial airliner finds that he is two degrees off the runway centerline halfway through his final approach, what course of action should he take? Is it best to make a single constant rate turn of two degrees to reach the runway on line? Or is it better to make a series of three

quick turns (i.e., four degrees one way, followed by three degrees in the opposite direction, followed by one degree back) to align his aircraft with the runway? The end result is exactly the same, but the impact to his passengers and crew, although not life threatening, could have been avoided had he chosen the slow, steady correction. The same rationale could be applied to the Federal Reserves' approach in establishing interest rate targets to achieve a desired level of inflation and promote output growth. Slow, deliberate policy implementation minimizes the short-run impacts to price setters, and thus consumers.

Suggestions for Future Research

Several suggestions for future research have already been introduced in the text of this study, but are restated for clarity. The first recognizes the probable bias of using aggregate or consensus data to examine RE in inflation forecasts. Use of panel data in the multivariate VAR framework would eliminate such bias and stratify the results of this study. Equally important is the inclusion of some proxy for private information variables in the VAR model. Although *private* information use, by its nature, is expected to be efficient, the inclusion of such a variable may alter the significance of coefficients estimated for the *public* information variables included in this study.

Another suggestion entails restricting coefficients of the reduced form VAR to create a structural VAR with component equations that better represent the dependent variables according to economic theory. This suggestion is related to furthering the work of Grant and Thomas (1999), in that it is possible to introduce information variables into the long-run cointegrating relation, and then examine vector error correction term coefficients, which is essentially a model of forecast errors. Using this approach, the forecast errors themselves can be separated into the component movements of inflation and inflation expectations.

Finally, the issue uncovered by the IRF simulation warrants further analysis. The question still remains as to whether the forecast error structure change of the early 1980's can be related directly to Fed policy approach changes, or if it is just a by-product of forecasting difficulties caused by the oil price shocks and inflation volatility of the 1970's.

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APPENDICES

APPENDIX A
DATA SOURCES, DEFINITIONS, AND DESCRIPTIONS

Data Sources and Definitions

Survey	Variable	Sample	Definition	Measure
SPF	y^e	1969-2001	Real GNP before 1992 Real GDP since 1992	Quarterly % Change
	π^e		Consumer Price Index	Quarterly % Change
	u^e		Civilian Unemployment Rate	Quarterly % Change
	i^e	1981-2001	3-Month Treasury Bill Rate	Quarterly % Change
LIV	y^e	1960-2000	Real GNP before 1992 Real GDP since 1992	Semiannual % Change
	π^e		Forecasted Consumer Price Index	Semiannual % Change
	u^e		Civilian Unemployment Rate	Semiannual % Change
Actuals	y	1960-2001	Real GNP before 1992 Real GDP since 1992	%Change Measurement Based on Survey Frequency
	π		Consumer Price Index	
	u		Civilian Unemployment Rate	
	i		3-Month Treasury Bill Rate	
	f		Federal Deficit/Surplus (log(rev)-log(exp))	
	g		Output Gap Variable (log(Potential/Actual))	
	s		Yield Spread (long - short term int rate)	
	m		M1 Money Supply	
	o		Relative Spot Price of Oil (CPI Energy/CPI-U)	

APPENDIX B
SINGLE EQUATION MODEL RESULTS
TESTS OF BIAS AND INEFFICIENCY

Tables 1 and 2 – Complete Bias Test Results

Dependent Variable: AINFPT
Sample(adjusted): 1969:4 2001:1

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.455184	0.261873	1.738186	0.0822
EINF	0.678577	0.259193	2.618036	0.0088
AR(1)	0.373014	0.042725	8.730642	0.0000
AR(3)	0.294854	0.094273	3.127646	0.0018
MA(8)	-0.267696	0.080850	-3.311040	0.0009
		Variance Equation		
C	0.071943	0.031127	2.311285	0.0208
ARCH(1)	0.489175	0.167284	2.924222	0.0035
(RESID<0)*ARCH(1)	-0.577432	0.171407	-3.368788	0.0008
GARCH(1)	0.497254	0.185140	2.685827	0.0072
R-squared	0.658840	Mean dependent var		1.247091
Adjusted R-squared	0.635513	S.D. dependent var		0.830726
S.E. of regression	0.501532	Akaike info criterion		1.382387
Sum squared resid	29.42958	Schwarz criterion		1.584979
Log likelihood	-78.09038	F-statistic		28.24342
Durbin-Watson stat	1.915570	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0 C(2)=1	
F-statistic	2.297536	Probability	0.105024
Chi-square	4.595072	Probability	0.100506

Dependent Variable: AINFPT
Sample(adjusted): 1971:1 1982:4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.824666	0.433630	1.901775	0.0639
EINF	0.702175	0.275227	2.551258	0.0144
AR(1)	0.232269	0.126875	1.830695	0.0741
AR(3)	0.453553	0.157560	2.878606	0.0062
AR(8)	-0.463235	0.112589	-4.114395	0.0002
R-squared	0.620799	Mean dependent var		1.892734
Adjusted R-squared	0.585524	S.D. dependent var		0.937294
S.E. of regression	0.603428	Akaike info criterion		1.925953
Sum squared resid	15.65740	Schwarz criterion		2.120870
Log likelihood	-41.22287	F-statistic		17.59906
Durbin-Watson stat	1.887499	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0 C(2)=1	
F-statistic	6.232726	Probability	0.004198
Chi-square	12.46545	Probability	0.001964

Dependent Variable: AINF
Sample(adjusted): 1962:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.440105	0.288388	1.526088	0.1314
EINF	0.958293	0.164371	5.830057	0.0000
AR(5)	-0.250054	0.111807	-2.236483	0.0285
AR(1)	0.315600	0.121722	2.592793	0.0116
MA(2)	0.384052	0.109140	3.518896	0.0008
R-squared	0.684179	Mean dependent var		2.330527
Adjusted R-squared	0.666386	S.D. dependent var		1.587132
S.E. of regression	0.916717	Akaike info criterion		2.727489
Sum squared resid	59.66623	Schwarz criterion		2.880827
Log likelihood	-98.64457	F-statistic		38.45270
Durbin-Watson stat	1.918674	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0 C(2)=1	
F-statistic	3.714407	Probability	0.029227
Chi-square	7.428814	Probability	0.024370

Dependent Variable: AINF
Sample(adjusted): 1960:2 1982:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.995135	0.695780	1.430244	0.1602
EINF	0.790747	0.287966	2.745974	0.0089
AR(1)	0.379696	0.199719	1.901148	0.0643
MA(2)	0.685333	0.177913	3.852070	0.0004
R-squared	0.757398	Mean dependent var		2.704244
Adjusted R-squared	0.739647	S.D. dependent var		1.922853
S.E. of regression	0.981132	Akaike info criterion		2.884468
Sum squared resid	39.46742	Schwarz criterion		3.045060
Log likelihood	-60.90053	F-statistic		42.66707
Durbin-Watson stat	1.745730	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0 C(2)=1	
F-statistic	1.334115	Probability	0.274584
Chi-square	2.668230	Probability	0.263391

Dependent Variable: AINF
Sample: 1983:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.369405	0.211838	1.743808	0.0908
EINF	0.742878	0.104669	7.097406	0.0000
AR(5)	-0.371080	0.129180	-2.872571	0.0072
R-squared	0.279633	Mean dependent var		1.641216
Adjusted R-squared	0.234610	S.D. dependent var		0.707458
S.E. of regression	0.618931	Akaike info criterion		1.960172
Sum squared resid	12.25843	Schwarz criterion		2.093487
Log likelihood	-31.30300	F-statistic		6.210886
Durbin-Watson stat	1.664256	Prob(F-statistic)		0.005259

Wald Test:

Null Hypothesis:		C(1)=0 C(2)=1	
F-statistic	4.199857	Probability	0.024008
Chi-square	8.399713	Probability	0.014998

Table 3 – Full Regression Results

Dependent Variable: AINFPT Sample(adjusted): 1969:4 2001:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.359824	0.454732	0.791289	0.4303
EINF	0.741968	0.370758	2.001219	0.0476
EGDP1	0.089679	0.185264	0.484062	0.6292
AR(1)	0.402322	0.114081	3.526624	0.0006
AR(3)	0.371464	0.113350	3.277154	0.0014
MA(8)	-0.290377	0.090529	-3.207544	0.0017
R-squared	0.667038	Mean dependent var		1.247091
Adjusted R-squared	0.653165	S.D. dependent var		0.830726
S.E. of regression	0.489237	Akaike info criterion		1.454508
Sum squared resid	28.72234	Schwarz criterion		1.589570
Log likelihood	-85.63403	F-statistic		48.08037
Durbin-Watson stat	1.996648	Prob(F-statistic)		0.000000
		Wald Test:		
Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0		
F-statistic	0.710264	Probability		0.547705
Chi-square	2.130793	Probability		0.545708

Dependent Variable: AINFPT Sample(adjusted): 1970:1 2001:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.504362	0.446296	1.130108	0.2607
EINF	0.653708	0.382204	1.710364	0.0898
D(EUNEMP1)	-0.224446	0.161770	-1.387440	0.1679
AR(1)	0.385855	0.103386	3.732175	0.0003
AR(3)	0.382182	0.107619	3.551258	0.0005
R-squared	0.653954	Mean dependent var		1.244130
Adjusted R-squared	0.642419	S.D. dependent var		0.833401
S.E. of regression	0.498358	Akaike info criterion		1.484182
Sum squared resid	29.80328	Schwarz criterion		1.597314
Log likelihood	-87.76137	F-statistic		56.69356
Durbin-Watson stat	1.932631	Prob(F-statistic)		0.000000
		Wald Test:		
Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0		
F-statistic	1.453831	Probability		0.230662
Chi-square	4.361494	Probability		0.224982

Dependent Variable: AINFPT Sample(adjusted): 1982:1 2001:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.326316	0.127774	2.553851	0.0127
EINF	0.628850	0.171851	3.659281	0.0005
D(ETBILL1)	0.262815	0.066988	3.923291	0.0002
R-squared	0.266849	Mean dependent var		0.818109
Adjusted R-squared	0.247034	S.D. dependent var		0.429299
S.E. of regression	0.372518	Akaike info criterion		0.901120
Sum squared resid	10.26897	Schwarz criterion		0.992437
Log likelihood	-31.69312	F-statistic		13.46711
Durbin-Watson stat	1.839578	Prob(F-statistic)		0.000010
Wald Test:				
Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0		
F-statistic	12.53644	Probability		0.000001
Chi-square	37.60933	Probability		0.000000

Dependent Variable: AINFPT Sample(adjusted): 1971:2 2001:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.261203	0.245019	1.066051	0.2887
EINF	0.847624	0.210292	4.030698	0.0001
AGDP1(-1)	0.085118	0.047322	1.798711	0.0747
AR(1)	0.373277	0.095775	3.897434	0.0002
AR(3)	0.395562	0.107007	3.696611	0.0003
AR(8)	-0.203892	0.073302	-2.781527	0.0063
R-squared	0.683366	Mean dependent var		1.246293
Adjusted R-squared	0.669478	S.D. dependent var		0.846756
S.E. of regression	0.486809	Akaike info criterion		1.446817
Sum squared resid	27.01606	Schwarz criterion		1.586191
Log likelihood	-80.80901	F-statistic		49.20734
Durbin-Watson stat	1.909071	Prob(F-statistic)		0.000000
Wald Test:				
Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0		
F-statistic	2.757778	Probability		0.045567
Chi-square	8.273333	Probability		0.040688

Dependent Variable: AINFPT Sample(adjusted): 1970:1 2001:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.040831	0.096072	0.425001	0.6716
EINF	0.597198	0.155854	3.831774	0.0002
AINFPT(-1)	0.438012	0.111253	3.937078	0.0001
AR(3)	0.358609	0.103462	3.466101	0.0007
MA(8)	-0.287978	0.086972	-3.311161	0.0012
R-squared	0.678281	Mean dependent var		1.244130
Adjusted R-squared	0.667557	S.D. dependent var		0.833401
S.E. of regression	0.480521	Akaike info criterion		1.411287
Sum squared resid	27.70808	Schwarz criterion		1.524420
Log likelihood	-83.20545	F-statistic		63.24909
Durbin-Watson stat	2.075727	Prob(F-statistic)		0.000000
		Wald Test:		
Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0		
F-statistic	7.793726	Probability		0.000085
Chi-square	23.38118	Probability		0.000034

Dependent Variable: AINFPT Sample(adjusted): 1971:3 2001:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.282599	0.239753	1.178708	0.2410
EINF	0.876442	0.210906	4.155604	0.0001
D(AUNEMP1(-1))	-0.409174	0.123405	-3.315696	0.0012
AR(1)	0.399993	0.086860	4.605007	0.0000
AR(3)	0.380479	0.101544	3.746921	0.0003
AR(8)	-0.192297	0.073293	-2.623675	0.0099
R-squared	0.704407	Mean dependent var		1.246262
Adjusted R-squared	0.691328	S.D. dependent var		0.850337
S.E. of regression	0.472432	Akaike info criterion		1.387260
Sum squared resid	25.22072	Schwarz criterion		1.527384
Log likelihood	-76.54196	F-statistic		53.85656
Durbin-Watson stat	1.954294	Prob(F-statistic)		0.000000
		Wald Test:		
Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0		
F-statistic	5.449871	Probability		0.001551
Chi-square	16.34961	Probability		0.000961

Dependent Variable: AINFPT
Sample(adjusted): 1971:3 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.214304	0.181548	1.180428	0.2403
EINF	0.940873	0.170177	5.528798	0.0000
D(ATBILL1(-1))	0.108350	0.027607	3.924685	0.0001
AR(1)	0.362236	0.093669	3.867193	0.0002
AR(3)	0.308534	0.100516	3.069509	0.0027
AR(8)	-0.218217	0.072600	-3.005729	0.0033

R-squared	0.710383	Mean dependent var	1.246262
Adjusted R-squared	0.697568	S.D. dependent var	0.850337
S.E. of regression	0.467633	Akaike info criterion	1.366837
Sum squared resid	24.71087	Schwarz criterion	1.506961
Log likelihood	-75.32681	F-statistic	55.43406
Durbin-Watson stat	1.979026	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	6.778326	Probability	0.000304
Chi-square	20.33498	Probability	0.000145

Dependent Variable: AINFPT
Sample(adjusted): 1971:2 2000:3

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.080940	0.089965	-0.899686	0.3702
EINF	1.334972	0.095066	14.04259	0.0000
AGAP(-1)	0.310837	0.051547	6.030167	0.0000
AR(1)	0.180532	0.090662	1.991267	0.0489
AR(2)	-0.196016	0.102797	-1.906820	0.0591
AR(3)	0.250621	0.079650	3.146517	0.0021
AR(8)	-0.253352	0.078709	-3.218833	0.0017

R-squared	0.716608	Mean dependent var	1.255254
Adjusted R-squared	0.701290	S.D. dependent var	0.850912
S.E. of regression	0.465061	Akaike info criterion	1.364192
Sum squared resid	24.00725	Schwarz criterion	1.528555
Log likelihood	-73.48735	F-statistic	46.78060
Durbin-Watson stat	1.971208	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	15.95301	Probability	0.000000
Chi-square	47.85902	Probability	0.000000

Dependent Variable: AINFPT
Sample(adjusted): 1971:2 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.499594	0.157352	3.175017	0.0019
EINF	0.959364	0.126480	7.585118	0.0000
YCURVE(-1)	-0.195046	0.042659	-4.572201	0.0000
AR(1)	0.253284	0.091051	2.781782	0.0063
AR(3)	0.281113	0.087892	3.198370	0.0018
AR(8)	-0.250890	0.083260	-3.013340	0.0032
R-squared	0.719688	Mean dependent var		1.246293
Adjusted R-squared	0.707393	S.D. dependent var		0.846756
S.E. of regression	0.458037	Akaike info criterion		1.324973
Sum squared resid	23.91696	Schwarz criterion		1.464348
Log likelihood	-73.49838	F-statistic		58.53788
Durbin-Watson stat	1.930265	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0	
F-statistic	7.990750	Probability	0.000070
Chi-square	23.97225	Probability	0.000025

Dependent Variable: AINFPT
Sample(adjusted): 1971:3 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.270745	0.226502	1.195333	0.2345
EINF	0.793457	0.193189	4.107148	0.0001
AMG(-1)	0.082508	0.030884	2.671529	0.0087
AR(1)	0.390934	0.097670	4.002614	0.0001
AR(3)	0.391727	0.102606	3.817758	0.0002
AR(8)	-0.216591	0.072320	-2.994887	0.0034
R-squared	0.689304	Mean dependent var		1.246262
Adjusted R-squared	0.675556	S.D. dependent var		0.850337
S.E. of regression	0.484352	Akaike info criterion		1.437094
Sum squared resid	26.50941	Schwarz criterion		1.577217
Log likelihood	-79.50707	F-statistic		50.13983
Durbin-Watson stat	1.909879	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0	
F-statistic	3.961657	Probability	0.009976
Chi-square	11.88497	Probability	0.007788

Table 4 – Full Regression Results

Dependent Variable: AINFPT
Sample(adjusted): 1971:3 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.364947	0.244294	1.493882	0.1380
EINF	0.844609	0.219238	3.852480	0.0002
AGDP1(-2)	-0.051729	0.059358	-0.871478	0.3853
AR(1)	0.388126	0.096943	4.003670	0.0001
AR(3)	0.363214	0.108444	3.349331	0.0011
AR(8)	-0.195177	0.080519	-2.423985	0.0169

R-squared	0.681289	Mean dependent var	1.246262
Adjusted R-squared	0.667186	S.D. dependent var	0.850337
S.E. of regression	0.490559	Akaike info criterion	1.462564
Sum squared resid	27.19327	Schwarz criterion	1.602687
Log likelihood	-81.02253	F-statistic	48.31054
Durbin-Watson stat	1.894796	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.282907	Probability	0.283739
Chi-square	3.848720	Probability	0.278270

Dependent Variable: AINFPT
Sample(adjusted): 1971:3 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.303878	0.232075	1.309397	0.1931
EINF	0.810250	0.273024	2.967683	0.0037
AINFPT(-2)	0.045293	0.136881	0.330893	0.7413
AR(1)	0.364365	0.093423	3.900166	0.0002
AR(3)	0.378695	0.114633	3.303550	0.0013
AR(8)	-0.215709	0.082433	-2.616795	0.0101

R-squared	0.678951	Mean dependent var	1.246262
Adjusted R-squared	0.664745	S.D. dependent var	0.850337
S.E. of regression	0.492355	Akaike info criterion	1.469871
Sum squared resid	27.39272	Schwarz criterion	1.609995
Log likelihood	-81.45734	F-statistic	47.79423
Durbin-Watson stat	1.899477	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.127464	Probability	0.341098
Chi-square	3.382392	Probability	0.336339

Dependent Variable: AINFPT
Sample(adjusted): 1971:4 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.340304	0.245912	1.383847	0.1692
EINF	0.838309	0.215407	3.891737	0.0002
D(EUNEMP1(-2))	0.021804	0.140078	0.155656	0.8766
AR(1)	0.373726	0.104033	3.592380	0.0005
AR(3)	0.383328	0.108551	3.531315	0.0006
AR(8)	-0.209261	0.079062	-2.646784	0.0093

R-squared	0.680876	Mean dependent var	1.250546
Adjusted R-squared	0.666629	S.D. dependent var	0.852672
S.E. of regression	0.492318	Akaike info criterion	1.470127
Sum squared resid	27.14626	Schwarz criterion	1.611009
Log likelihood	-80.73747	F-statistic	47.79208
Durbin-Watson stat	1.914904	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.154827	Probability	0.330339
Chi-square	3.464480	Probability	0.325398

Dependent Variable: AINFPT
Sample(adjusted): 1971:4 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.371107	0.272268	1.363021	0.1756
EINF	0.811348	0.234016	3.467062	0.0007
D(ATBILL1(-2))	-0.025469	0.031705	-0.803316	0.4235
AR(1)	0.406736	0.093862	4.333355	0.0000
AR(3)	0.361450	0.119331	3.028973	0.0030
AR(8)	-0.199366	0.080013	-2.491653	0.0142

R-squared	0.682191	Mean dependent var	1.250546
Adjusted R-squared	0.668003	S.D. dependent var	0.852672
S.E. of regression	0.491303	Akaike info criterion	1.465996
Sum squared resid	27.03437	Schwarz criterion	1.606879
Log likelihood	-80.49379	F-statistic	48.08258
Durbin-Watson stat	1.922232	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.627153	Probability	0.187101
Chi-square	4.881460	Probability	0.180686

Dependent Variable: AINFPT
Sample(adjusted): 1971:4 2000:4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.350859	0.266189	1.318083	0.1902
EINF	0.827989	0.230796	3.587539	0.0005
D(AGAP(-2))	-0.082651	0.154566	-0.534731	0.5939
AR(1)	0.385172	0.097892	3.934680	0.0001
AR(3)	0.373528	0.112144	3.330778	0.0012
AR(8)	-0.196388	0.080783	-2.431062	0.0167

R-squared	0.681422	Mean dependent var	1.253892
Adjusted R-squared	0.667072	S.D. dependent var	0.855561
S.E. of regression	0.493658	Akaike info criterion	1.475974
Sum squared resid	27.05053	Schwarz criterion	1.617624
Log likelihood	-80.34447	F-statistic	47.48472
Durbin-Watson stat	1.893245	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.156177	Probability	0.329858
Chi-square	3.468531	Probability	0.324867

Dependent Variable: AINFPT
Sample(adjusted): 1971:3 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.361687	0.191798	1.885768	0.0619
EINF	0.928685	0.152987	6.070368	0.0000
YCURVE(-2)	-0.085501	0.057054	-1.498603	0.1368
AR(1)	0.289370	0.094122	3.074424	0.0026
AR(3)	0.377020	0.102912	3.663535	0.0004
AR(8)	-0.238760	0.082268	-2.902214	0.0045

R-squared	0.685367	Mean dependent var	1.246262
Adjusted R-squared	0.671445	S.D. dependent var	0.850337
S.E. of regression	0.487410	Akaike info criterion	1.449683
Sum squared resid	26.84527	Schwarz criterion	1.589807
Log likelihood	-80.25616	F-statistic	49.22978
Durbin-Watson stat	1.922626	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	2.103449	Probability	0.103744
Chi-square	6.310346	Probability	0.097450

Dependent Variable: AINFPT
Sample(adjusted): 1971:4 2001:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.348678	0.253759	1.374055	0.1722
EINF	0.780017	0.222698	3.502585	0.0007
AMG(-2)	0.042286	0.041233	1.025550	0.3073
AR(1)	0.369761	0.094072	3.930618	0.0001
AR(3)	0.404490	0.107930	3.747692	0.0003
AR(8)	-0.207768	0.076134	-2.728984	0.0074

R-squared	0.683488	Mean dependent var	1.250546
Adjusted R-squared	0.669358	S.D. dependent var	0.852672
S.E. of regression	0.490299	Akaike info criterion	1.461906
Sum squared resid	26.92403	Schwarz criterion	1.602789
Log likelihood	-80.25248	F-statistic	48.37144
Durbin-Watson stat	1.948612	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.287762	Probability	0.282147
Chi-square	3.863287	Probability	0.276610

Table 5 – Full Regression Results

Dependent Variable: AINFSA
Sample(adjusted): 1972:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.094846	0.793140	0.119583	0.9053
EINF	1.016087	0.303143	3.351835	0.0015
EGDP	0.114707	0.139827	0.820353	0.4157
AR(1)	0.542010	0.156587	3.461409	0.0011

R-squared	0.691306	Mean dependent var	2.558261
Adjusted R-squared	0.673832	S.D. dependent var	1.656025
S.E. of regression	0.945774	Akaike info criterion	2.793965
Sum squared resid	47.40789	Schwarz criterion	2.937337
Log likelihood	-75.62801	F-statistic	39.56361
Durbin-Watson stat	2.049277	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	0.768555	Probability	0.516754
Chi-square	2.305664	Probability	0.511437

Dependent Variable: AINFSA
Sample(adjusted): 1962:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.574449	0.462399	1.242322	0.2181
EINF	0.893964	0.229417	3.896680	0.0002
D(EUNEMP1)	0.171347	0.222408	0.770419	0.4436
AR(1)	0.573551	0.125438	4.572400	0.0000

R-squared	0.719030	Mean dependent var	2.328308
Adjusted R-squared	0.707323	S.D. dependent var	1.542241
S.E. of regression	0.834347	Akaike info criterion	2.526861
Sum squared resid	50.12170	Schwarz criterion	2.649531
Log likelihood	-92.02072	F-statistic	61.41834
Durbin-Watson stat	2.042365	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.239894	Probability	0.301611
Chi-square	3.719681	Probability	0.293368

Dependent Variable: AINFSA
Sample(adjusted): 1961:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.531235	0.469973	1.130354	0.2620
EINF	0.902380	0.222209	4.060949	0.0001
AGDP(-1)	0.012218	0.081007	0.150822	0.8805
AR(1)	0.575340	0.129082	4.457164	0.0000

R-squared	0.723069	Mean dependent var	2.285759
Adjusted R-squared	0.711842	S.D. dependent var	1.544803
S.E. of regression	0.829255	Akaike info criterion	2.513343
Sum squared resid	50.88717	Schwarz criterion	2.634200
Log likelihood	-94.02039	F-statistic	64.40490
Durbin-Watson stat	2.079366	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.234415	Probability	0.303332
Chi-square	3.703244	Probability	0.295343

Dependent Variable: AINFSA
Sample(adjusted): 1961:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.770844	0.797737	0.966289	0.3370
EINF	0.962432	0.292864	3.286280	0.0016
AINFSA(-1)	-0.142864	0.187665	-0.761273	0.4489
AR(1)	0.664063	0.203946	3.256073	0.0017

R-squared	0.725151	Mean dependent var	2.285759
Adjusted R-squared	0.714008	S.D. dependent var	1.544803
S.E. of regression	0.826133	Akaike info criterion	2.505799
Sum squared resid	50.50469	Schwarz criterion	2.626655
Log likelihood	-93.72614	F-statistic	65.07946
Durbin-Watson stat	1.985179	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	0.748347	Probability	0.526751
Chi-square	2.245042	Probability	0.523131

Dependent Variable: AINFSA
Sample(adjusted): 1961:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.533886	0.452572	1.179672	0.2419
EINF	0.909077	0.228353	3.981009	0.0002
D(AUNEM(-1))	-0.118664	0.224932	-0.527556	0.5994
AR(1)	0.576754	0.131719	4.378674	0.0000

R-squared	0.724898	Mean dependent var	2.285759
Adjusted R-squared	0.713745	S.D. dependent var	1.544803
S.E. of regression	0.826512	Akaike info criterion	2.506717
Sum squared resid	50.55108	Schwarz criterion	2.627574
Log likelihood	-93.76195	F-statistic	64.99710
Durbin-Watson stat	2.099252	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.186284	Probability	0.320868
Chi-square	3.558853	Probability	0.313209

Dependent Variable: AINFSA
Sample(adjusted): 1961:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.574548	0.473073	1.214500	0.2284
EINF	0.891105	0.235331	3.786595	0.0003
D(ATBILL(-1))	0.017617	0.055001	0.320310	0.7496
AR(1)	0.572796	0.130914	4.375356	0.0000

R-squared	0.723501	Mean dependent var	2.285759
Adjusted R-squared	0.712291	S.D. dependent var	1.544803
S.E. of regression	0.828609	Akaike info criterion	2.511783
Sum squared resid	50.80786	Schwarz criterion	2.632640
Log likelihood	-93.95955	F-statistic	64.54395
Durbin-Watson stat	2.075475	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.079508	Probability	0.363121
Chi-square	3.238525	Probability	0.356291

Dependent Variable: AINFSA
Sample(adjusted): 1964:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.119776	0.341911	-0.350314	0.7272
EINF	1.236575	0.172060	7.186865	0.0000
AGAPV(-1)	0.533774	0.109096	4.892715	0.0000
AR(1)	0.278406	0.139794	1.991540	0.0504
AR(7)	0.283352	0.124623	2.273669	0.0261

R-squared	0.778490	Mean dependent var	2.392478
Adjusted R-squared	0.765460	S.D. dependent var	1.539771
S.E. of regression	0.745701	Akaike info criterion	2.317050
Sum squared resid	37.81274	Schwarz criterion	2.473931
Log likelihood	-79.57232	F-statistic	59.74602
Durbin-Watson stat	2.025720	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	9.952042	Probability	0.000016
Chi-square	29.85613	Probability	0.000001

Dependent Variable: AINFSA
Sample(adjusted): 1960:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.693899	0.238014	2.915365	0.0047
EINF	1.050537	0.146073	7.191867	0.0000
YCURVE(-1)	-0.328496	0.110156	-2.982097	0.0038

R-squared	0.692158	Mean dependent var	2.237061
Adjusted R-squared	0.684163	S.D. dependent var	1.556454
S.E. of regression	0.874718	Akaike info criterion	2.606949
Sum squared resid	58.91516	Schwarz criterion	2.696275
Log likelihood	-101.2780	F-statistic	86.56433
Durbin-Watson stat	1.203404	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	4.255510	Probability	0.007778
Chi-square	12.76653	Probability	0.005170

Dependent Variable: AINFSA
Sample(adjusted): 1961:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.407701	0.455255	0.895544	0.3734
EINF	0.864738	0.249372	3.467665	0.0009
AM1GR(-1)	0.082406	0.050378	1.635755	0.1061
AR(1)	0.602128	0.129096	4.664194	0.0000

R-squared	0.730490	Mean dependent var	2.285759
Adjusted R-squared	0.719564	S.D. dependent var	1.544803
S.E. of regression	0.818069	Akaike info criterion	2.486179
Sum squared resid	49.52349	Schwarz criterion	2.607036
Log likelihood	-92.96100	F-statistic	66.85759
Durbin-Watson stat	2.089537	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.643526	Probability	0.186632
Chi-square	4.930579	Probability	0.176952

Table 6 – Full Regression Results

Dependent Variable: AINFSA
Sample(adjusted): 1962:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.142106	0.487812	0.291312	0.7716
EINF	1.007172	0.210682	4.780525	0.0000
AGDP(-2)	0.113041	0.081407	1.388585	0.1692
AR(1)	0.529009	0.130996	4.038356	0.0001
R-squared	0.727288	Mean dependent var		2.306728
Adjusted R-squared	0.716081	S.D. dependent var		1.543719
S.E. of regression	0.822556	Akaike info criterion		2.497751
Sum squared resid	49.39174	Schwarz criterion		2.619507
Log likelihood	-92.16341	F-statistic		64.89390
Durbin-Watson stat	2.092722	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0		
		C(2)=1		
		C(3)=0		
F-statistic	1.958538	Probability		0.127741
Chi-square	5.875614	Probability		0.117821

Dependent Variable: AINFSA
Sample(adjusted): 1962:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.572610	0.453662	1.262194	0.2109
EINF	0.787549	0.303453	2.595296	0.0114
AINFSA(-2)	0.089647	0.171556	0.522554	0.6029
AR(1)	0.576198	0.128598	4.480630	0.0000
R-squared	0.720624	Mean dependent var		2.306728
Adjusted R-squared	0.709143	S.D. dependent var		1.543719
S.E. of regression	0.832545	Akaike info criterion		2.521892
Sum squared resid	50.59863	Schwarz criterion		2.643648
Log likelihood	-93.09285	F-statistic		62.76563
Durbin-Watson stat	2.020236	Prob(F-statistic)		0.000000

Wald Test:

Null Hypothesis:		C(1)=0		
		C(2)=1		
		C(3)=0		
F-statistic	1.049281	Probability		0.376049
Chi-square	3.147842	Probability		0.369388

Dependent Variable: AINFSA
Sample(adjusted): 1962:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.471473	0.426120	1.106432	0.2722
EINF	0.937424	0.208614	4.493573	0.0000
D(AUNEM(-2))	-0.163799	0.171733	-0.953801	0.3433
AR(1)	0.556641	0.130004	4.281735	0.0001

R-squared	0.722594	Mean dependent var	2.306728
Adjusted R-squared	0.711193	S.D. dependent var	1.543719
S.E. of regression	0.829606	Akaike info criterion	2.514818
Sum squared resid	50.24195	Schwarz criterion	2.636574
Log likelihood	-92.82049	F-statistic	63.38397
Durbin-Watson stat	2.106643	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.688011	Probability	0.177050
Chi-square	5.064033	Probability	0.167168

Dependent Variable: AINFSA
Sample(adjusted): 1962:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.512305	0.428634	1.195204	0.2359
EINF	0.920214	0.215482	4.270498	0.0001
D(ATBILL(-2))	0.042010	0.035353	1.188298	0.2386
AR(1)	0.558513	0.126561	4.413010	0.0000

R-squared	0.722080	Mean dependent var	2.306728
Adjusted R-squared	0.710659	S.D. dependent var	1.543719
S.E. of regression	0.830373	Akaike info criterion	2.516667
Sum squared resid	50.33491	Schwarz criterion	2.638423
Log likelihood	-92.89167	F-statistic	63.22196
Durbin-Watson stat	2.101620	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	1.882479	Probability	0.140054
Chi-square	5.647436	Probability	0.130081

Dependent Variable: AINFSA
Sample(adjusted): 1964:2 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.267191	0.431224	0.619611	0.5376
EINF	1.067799	0.206142	5.179915	0.0000
AGAPV(-2)	0.484665	0.111623	4.341987	0.0000
AR(1)	0.368850	0.140515	2.624978	0.0107
AR(7)	0.233183	0.137439	1.696634	0.0944

R-squared	0.759734	Mean dependent var	2.421212
Adjusted R-squared	0.745390	S.D. dependent var	1.530741
S.E. of regression	0.772395	Akaike info criterion	2.388275
Sum squared resid	39.97183	Schwarz criterion	2.546376
Log likelihood	-80.97789	F-statistic	52.96442
Durbin-Watson stat	2.048038	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	7.212979	Probability	0.000288
Chi-square	21.63894	Probability	0.000078

Dependent Variable: AINFSA
Sample(adjusted): 1961:1 2000:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.565115	0.241731	2.337781	0.0220
EINF	1.063929	0.154418	6.889915	0.0000
YCURVE(-2)	-0.254411	0.090516	-2.810685	0.0063

R-squared	0.659892	Mean dependent var	2.256826
Adjusted R-squared	0.650942	S.D. dependent var	1.556264
S.E. of regression	0.919458	Akaike info criterion	2.707170
Sum squared resid	64.25065	Schwarz criterion	2.797149
Log likelihood	-103.9332	F-statistic	73.72929
Durbin-Watson stat	1.010325	Prob(F-statistic)	0.000000

Wald Test:

Null Hypothesis: C(1)=0
C(2)=1
C(3)=0

F-statistic	4.210387	Probability	0.008250
Chi-square	12.63116	Probability	0.005506

Dependent Variable: AINFSA Sample(adjusted): 1962:1 2000:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.454178	0.434509	1.045266	0.2993
EINF	0.891436	0.213614	4.173125	0.0001
AM1GR(-2)	0.044024	0.061714	0.713357	0.4779
AR(1)	0.577155	0.126052	4.578710	0.0000
R-squared	0.721233	Mean dependent var		2.306728
Adjusted R-squared	0.709777	S.D. dependent var		1.543719
S.E. of regression	0.831638	Akaike info criterion		2.519711
Sum squared resid	50.48836	Schwarz criterion		2.641467
Log likelihood	-93.00885	F-statistic		62.95587
Durbin-Watson stat	2.089635	Prob(F-statistic)		0.000000
		Wald Test:		
Null Hypothesis:		C(1)=0 C(2)=1 C(3)=0		
F-statistic	1.094003	Probability		0.357198
Chi-square	3.282008	Probability		0.350155

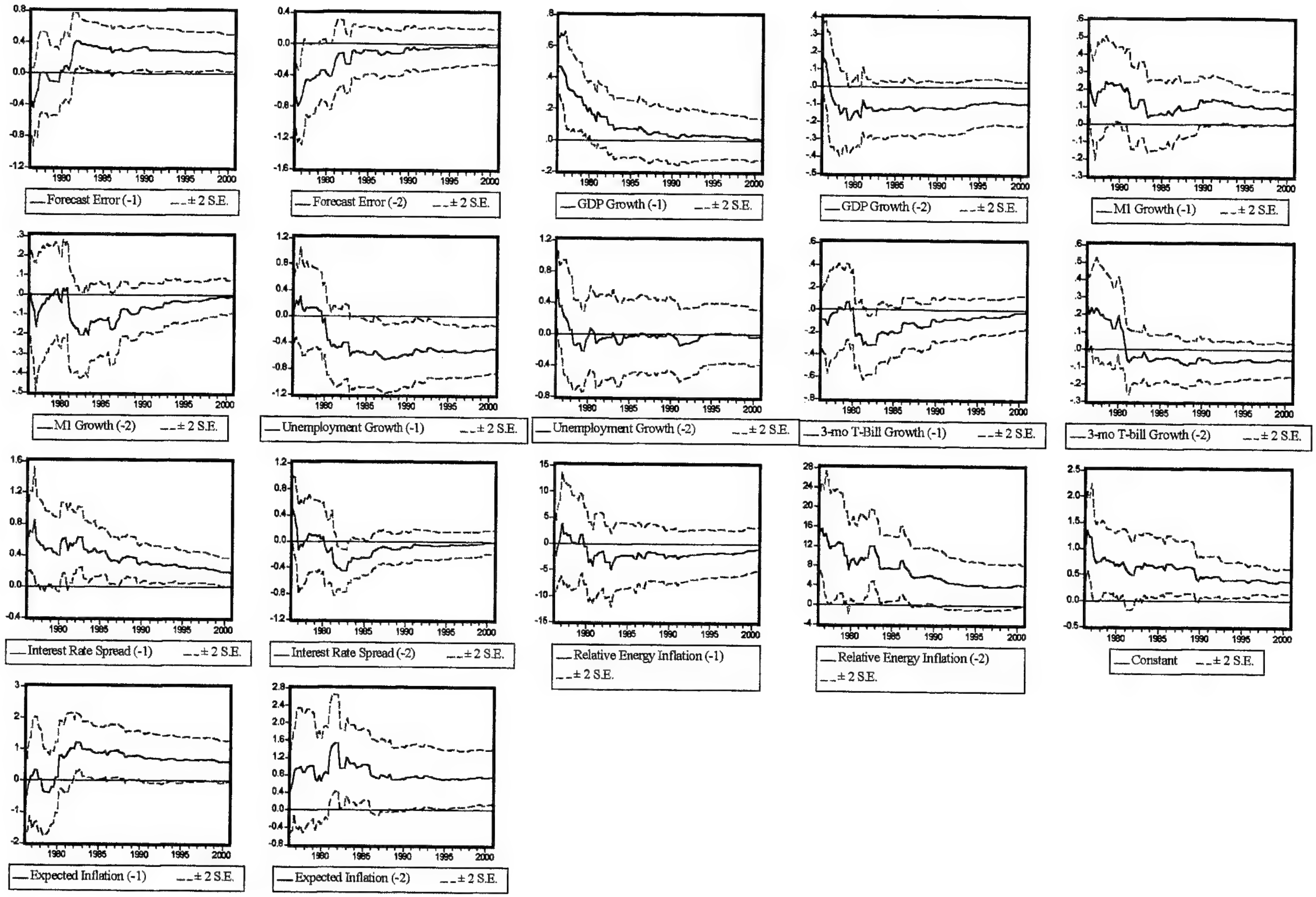
APPENDIX C
SINGLE EQUATION SPECIFICATION ROBUSTNESS AND STABILITY TESTS

Single Equation Specification Robustness Testing – Survey of Professional Forecasters

Dependent Variable	Sample Period	ε^{π}	$\Delta\pi^{e}$	$\Delta\pi_t$	Δy	Δm	Δu	Δi	s	Δo	β_0
ε^{π}_{t}	1969-2001	.27** -.02	.62* .78**	------	.01 -.09	.09** .00	-.49** -.03	-.02 -.05	.19** .00	-.92 3.92*	.36**
ε^{π}_{t}	1969-2001	.20* .03	------	------	-.01 -.09	.09 .00	-.44** -.06	.05 -.05	.17** .04	-.81 4.90**	.40**
$\Delta\pi_t$	1969-2001	------	.34 .67**	-.59** -.34**	.03 -.07	.09 .00	-.72** -.03	-.10 -.03	.25** -.13	-1.60 .57	.08
ε^{π}_{t}	1969-1982	.37** -.25	1.22** .97**	------	.10 -.14*	.14 -.20*	-.39 -.03	-.31 -.04	.63** -.44**	-3.50 12.08**	.65**
ε^{π}_{t}	1969-1982	.22 -.14	------	------	.11 -.10	.10 -.22*	-.29 -.07	-.25* -.07	.67** -.38**	-2.88 12.92**	.83**
$\Delta\pi_t$	1969-1982	------	.95** 1.12**	-.43** -.23	.06 -.11	.17 -.14	-.52* -.04	-.31** .02	.60** -.60**	-4.38 7.35**	.03
ε^{π}_{t}	1983-2001	.01 .05	-.71 -.37	------	-.06 -.03	.04 -.01	-.23 .00	.11 .06	-.09 .21**	.78 .50	.29*
ε^{π}_{t}	1983-2001	.08 .00	------	------	-.05 .00	.05 -.02	-.23 .07	.09 .05	-.08 .20**	-.09 -.24	.26*
$\Delta\pi_t$	1983-2001	------	-1.48* -.81*	-.86** -.61**	.02 -.14	.03 .04	-.67* -.05	.01 .11	.00 .13	1.21 .52	.19

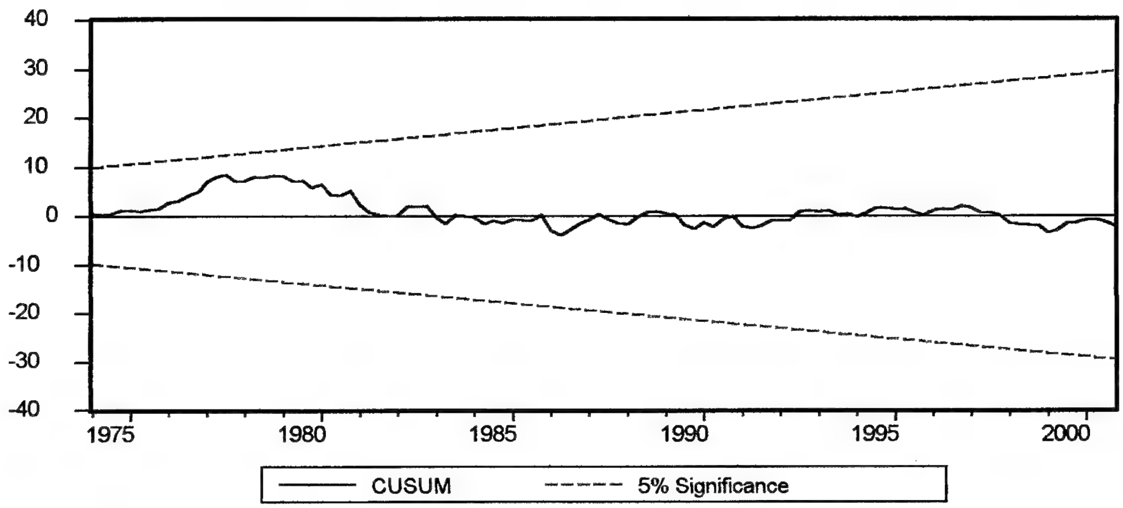
* Denotes 10% level of significance
** Denotes 5% level of significance
"Boxed" model indicates equation used for recursive coefficient calculation on the following page
Each coefficient listed in the independent variable section represents a successive lag of that variable in the equation

Recursive Coefficients – Survey of Professional Forecasters



Stability Tests – CUSUM and Chow Break-point Test

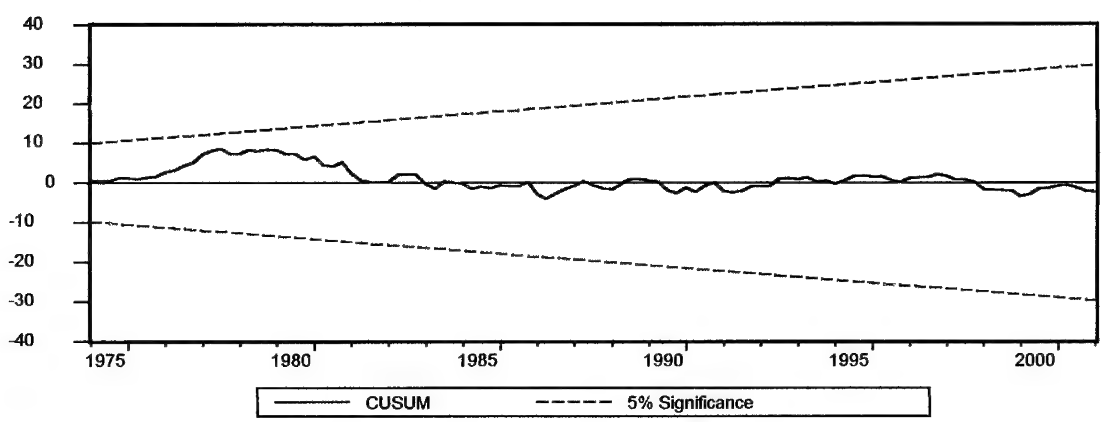
Equation: $\Delta\pi_t = \beta_0 + \beta_1\Delta\pi_{t-1} + \beta_2\Delta\pi_{t-2} + \beta_3\Delta y_{t-1} + \beta_4\Delta y_{t-2} + \beta_5\Delta m_{t-1} + \beta_6\Delta m_{t-2} + \beta_7\Delta u_{t-1} + \beta_8\Delta u_{t-2} + \beta_9\Delta i_{t-1} + \beta_{10}\Delta i_{t-2} + \beta_{11}s_{t-1} + \beta_{12}s_{t-2} + \beta_{13}o_{t-2} + \beta_{14}o_{t-2} + \beta_{15}\pi_t^{e} + \varepsilon^{\pi}_t$



Chow Breakpoint Test: 1983:1

F-statistic	2.926498	Probability	0.000506
Log likelihood ratio	54.46724	Probability	0.000008

Equation: $\varepsilon^{\pi}_t = \beta_0 + \beta_1\varepsilon^{\pi}_{t-1} + \beta_2\varepsilon^{\pi}_{t-2} + \beta_3\Delta y_{t-1} + \beta_4\Delta y_{t-2} + \beta_5\Delta m_{t-1} + \beta_6\Delta m_{t-2} + \beta_7\Delta u_{t-1} + \beta_8\Delta u_{t-2} + \beta_9\Delta i_{t-1} + \beta_{10}\Delta i_{t-2} + \beta_{11}s_{t-1} + \beta_{12}s_{t-2} + \beta_{13}o_{t-2} + \beta_{14}o_{t-2} + \beta_{15}\pi_t^{e} + \varepsilon_t$



Chow Breakpoint Test: 1983:1

F-statistic	2.495759	Probability	0.002789
Log likelihood ratio	47.78418	Probability	0.000093

APPENDIX D
PHILLIPS-PERRON
UNIT ROOT TESTS

Real GDP Log level first difference – Intercept Only

PP Test Statistic	-8.737039	1% Critical Value*	-3.4823
		5% Critical Value	-2.8840
		10% Critical Value	-2.5786

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)
Residual variance with no correction	0.731276
Residual variance with correction	0.845065

Consumer Price Index Log level first difference – Intercept Only

PP Test Statistic	-4.065383	1% Critical Value*	-3.4823
		5% Critical Value	-2.8840
		10% Critical Value	-2.5786

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)
Residual variance with no correction	0.297259
Residual variance with correction	0.263969

Unemployment Rate Levels – Trend and Intercept

PP Test Statistic	-2.613748	1% Critical Value*	-4.0320
		5% Critical Value	-3.4452
		10% Critical Value	-3.1473

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)
Residual variance with no correction	0.129587
Residual variance with correction	0.284433

3-Month Treasury Bill Rate – Intercept Only

PP Test Statistic	-2.622772	1% Critical Value*	-3.4823
		5% Critical Value	-2.8840
		10% Critical Value	-2.5786

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)
Residual variance with no correction	1.557432
Residual variance with correction	1.318159

Federal Deficit/Surplus Log level difference of federal revenues and outlays – No intercept or trend

PP Test Statistic	-7.745599	1% Critical Value*	-3.4835
		5% Critical Value	-2.8845
		10% Critical Value	-2.5789

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)
Residual variance with no correction	221.2206
Residual variance with correction	245.0849

Output Gap Log (Actual GDP/Potential GDP) – No intercept or trend

PP Test Statistic	-2.817650	1% Critical Value*	-2.5821
		5% Critical Value	-1.9425
		10% Critical Value	-1.6170

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)
Residual variance with no correction	0.140170
Residual variance with correction	0.257699

Yield Spread (Level 10 Year Treasury Bond – 3 Month Treasury Bill) – Intercept Only

PP Test Statistic	-3.976322	1% Critical Value*	-3.4826
		5% Critical Value	-2.8842
		10% Critical Value	-2.5787

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)	
Residual variance with no correction		0.747727
Residual variance with correction		0.728573

M1 Log level first difference – Trend and intercept

PP Test Statistic	-6.500282	1% Critical Value*	-4.0325
		5% Critical Value	-3.4455
		10% Critical Value	-3.1474

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)	
Residual variance with no correction		1.135098
Residual variance with correction		1.219884

Relative Price of Oil (log level difference of US $/bbl – CPI) – No intercept or trend

PP Test Statistic	-11.64214	1% Critical Value*	-2.5819
		5% Critical Value	-1.9424
		10% Critical Value	-1.6170

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)	
Residual variance with no correction		353.1364
Residual variance with correction		358.7566

Slope of the Yield Curve (10 year bond/3 month Tbill)

PP Test Statistic	-3.976322	1% Critical Value*	-3.4826
		5% Critical Value	-2.8842
		10% Critical Value	-2.5787

*MacKinnon critical values for rejection of hypothesis of a unit root.

Lag truncation for Bartlett kernel: 4	(Newey-West suggests: 4)
Residual variance with no correction	0.747727
Residual variance with correction	0.728573

APPENDIX E
REDUCED FORM
MULTIVARIATE VAR RESULTS

SPF Model Including the Relative Price of Energy and Exogenous Inflation Expectations

	Forecast Errors of Inflation	Real GDP Growth	M1 Money Growth	Unemp Rt Growth	3-Month T-Bill Growth	Yield Curve Slope Growth	Relative Price of Energy
FE (-1)	0.1878	0.1931	0.3885	0.1461	-0.5732	-0.2075	0.0111
	-0.1129	-0.1924	-0.2214	-0.0742	-0.2750	-0.1916	-0.0059
	[1.66318]	[1.00374]	[1.75486]	[1.96941]	[-2.08411]	[-1.08256]	[1.88531]
FE (-2)	0.0616	-0.4595	-0.4288	0.1159	0.7840	0.6298	0.0006
	-0.1069	-0.1822	-0.2097	-0.0703	-0.2605	-0.1815	-0.0056
	[0.57636]	[-2.52181]	[-2.04533]	[1.64936]	[3.00997]	[3.46970]	[0.11409]
y (-1)	-0.0172	0.1191	-0.0162	-0.1009	0.2156	0.0989	0.0006
	-0.0671	-0.1143	-0.1315	-0.0441	-0.1634	-0.1138	-0.0035
	[-0.25660]	[1.04236]	[-0.12333]	[-2.28936]	[1.31950]	[0.86912]	[0.17389]
y (-2)	-0.0933	0.0695	-0.0641	-0.0236	0.1085	0.1701	-0.0018
	-0.0630	-0.1073	-0.1235	-0.0414	-0.1534	-0.1069	-0.0033
	[-1.48204]	[0.64796]	[-0.51887]	[-0.56940]	[0.70724]	[1.59133]	[-0.56563]
m (-1)	0.1034	-0.1421	0.3531	0.0123	-0.0241	0.0403	-0.0001
	-0.0448	-0.0764	-0.0879	-0.0295	-0.1092	-0.0761	-0.0023
	[2.30537]	[-1.85975]	[4.01603]	[0.41839]	[-0.22068]	[0.52973]	[-0.04050]
m (-2)	0.0066	0.1040	0.2902	-0.0436	0.0942	-0.0806	-0.0003
	-0.0431	-0.0734	-0.0845	-0.0283	-0.1050	-0.0731	-0.0022
	[0.15405]	[1.41609]	[3.43472]	[-1.54057]	[0.89787]	[-1.10229]	[-0.11232]
u (-1)	-0.3995	-0.7215	0.0239	0.2791	-1.1930	-0.9331	-0.0158
	-0.1893	-0.3226	-0.3712	-0.1244	-0.4611	-0.3213	-0.0098
	[-2.11037]	[-2.23666]	[0.06449]	[2.24348]	[-2.58713]	[-2.90398]	[-1.61128]
u (-2)	-0.0438	0.1072	0.3507	0.1436	-0.1205	0.3318	0.0092
	-0.1774	-0.3022	-0.3477	-0.1166	-0.4320	-0.3010	-0.0092
	[-0.24697]	[0.35459]	[1.00856]	[1.23176]	[-0.27901]	[1.10229]	[0.99565]
i (-1)	0.0693	-0.2270	-0.6494	0.0910	-0.4904	-0.3283	0.0017
	-0.0737	-0.1255	-0.1444	-0.0484	-0.1794	-0.1250	-0.0038
	[0.94086]	[-1.80866]	[-4.49685]	[1.87915]	[-2.73328]	[-2.62607]	[0.45538]
i (-2)	-0.0408	-0.1802	0.1197	0.0585	-0.4461	-0.2281	0.0010
	-0.0493	-0.0839	-0.0965	-0.0324	-0.1199	-0.0836	-0.0026
	[-0.82772]	[-2.14710]	[1.23986]	[1.80761]	[-3.71925]	[-2.72914]	[0.39635]
s (-1)	0.1560	0.1525	0.4131	-0.0309	0.2311	1.0788	-0.0001
	-0.0912	-0.1555	-0.1789	-0.0600	-0.2222	-0.1548	-0.0047
	[1.71007]	[0.98093]	[2.30981]	[-0.51535]	[1.04001]	[6.96721]	[-0.03134]
s (-2)	0.0625	-0.2667	-0.5174	0.0275	-0.0708	-0.1896	0.0026
	-0.0929	-0.1583	-0.1821	-0.0611	-0.2263	-0.1577	-0.0048
	[0.67293]	[-1.68452]	[-2.84110]	[0.44995]	[-0.31267]	[-1.20268]	[0.54084]
o (-1)	-0.3755	-2.0692	-10.1361	-3.0752	5.7649	4.3369	0.0285
	-2.0906	-3.5623	-4.0985	-1.3738	-5.0920	-3.5483	-0.1085
	[-0.17960]	[-0.58086]	[-2.47308]	[-2.23850]	[1.13215]	[1.22227]	[0.26291]
o (-2)	5.3224	5.9467	3.3984	-1.4888	1.9554	-3.5942	-0.0269
	-2.1781	-3.7113	-4.2700	-1.4312	-5.3050	-3.6967	-0.1131
	[2.44361]	[1.60232]	[0.79589]	[-1.04021]	[0.36859]	[-0.97229]	[-0.23806]
Constant	0.5496	0.4508	-0.1255	0.0375	-0.3561	-0.4692	-0.0007
	-0.1583	-0.2697	-0.3103	-0.1040	-0.3855	-0.2686	-0.0082
	[3.47292]	[1.67175]	[-0.40449]	[0.36053]	[-0.92374]	[-1.74702]	[-0.08881]
Inf Exp Growth	-0.1491	0.0869	0.4650	0.0508	0.1872	0.0747	0.0041
	-0.1059	-0.1805	-0.2076	-0.0696	-0.2580	-0.1798	-0.0055
	[-1.40741]	[0.48135]	[2.23954]	[0.72944]	[0.72564]	[0.41582]	[0.74563]
R-squared	0.4984	0.3774	0.6166	0.4721	0.3894	0.7195	0.2157
Adj. R-squared	0.4294	0.2917	0.5639	0.3994	0.3054	0.6810	0.1078
Sum sq. resids	21.5793	62.6540	82.9354	9.3176	128.0147	62.1598	0.0581
S.E. equation	0.4449	0.7582	0.8723	0.2924	1.0837	0.7552	0.0231
F-statistic	7.2215	4.4046	11.6876	6.4978	4.6338	18.6437	1.9983

SPF Model Including the Relative Price of Energy and Exogenous Inflation Expectations

	Forecast Errors of Inflation	Real GDP Growth	M1 Money Growth	Unemp Rt Growth	3-Month T-Bill Growth	Yield Curve Slope Growth
FE (-1)	0.1607	0.1226	0.1298	0.0761	-0.4391	-0.0896
	-0.1021	-0.1715	-0.2006	-0.0672	-0.2436	-0.1704
	[1.57499]	[0.71513]	[0.64695]	[1.13318]	[-1.80237]	[-0.52557]
FE (-2)	**0.1943**	-0.3195	-0.3932	0.0630	0.8621	0.5604
	-0.0931	-0.1564	-0.1829	-0.0613	-0.2222	-0.1554
	[2.08791]	[-2.04317]	[-2.14996]	[1.02866]	[3.88007]	[3.60622]
y (-1)	-0.0447	0.0799	-0.0847	-0.1096	0.2358	0.1385
	-0.0664	-0.1116	-0.1306	-0.0437	-0.1586	-0.1109
	[-0.67341]	[0.71560]	[-0.64900]	[-2.50575]	[1.48693]	[1.24880]
y (-2)	-0.0892	0.0688	-0.0930	-0.0348	0.1288	0.1803
	-0.0637	-0.1070	-0.1252	-0.0419	-0.1521	-0.1064
	[-1.40066]	[0.64318]	[-0.74265]	[-0.83098]	[0.84684]	[1.69499]
m (-1)	0.0819	-0.1629	0.3583	0.0244	-0.0433	0.0470
	-0.0446	-0.0749	-0.0876	-0.0293	-0.1064	-0.0744
	[1.83856]	[-2.17626]	[4.09163]	[0.83259]	[-0.40690]	[0.63166]
m (-2)	0.0073	0.1062	0.2995	-0.0409	0.0891	-0.0847
	-0.0438	-0.0736	-0.0861	-0.0288	-0.1046	-0.0732
	[0.16548]	[1.44188]	[3.47814]	[-1.41879]	[0.85202]	[-1.15793]
u (-1)	**-0.5210**	-0.8761	-0.1670	0.2766	-1.1700	-0.8043
	-0.1845	-0.3099	-0.3625	-0.1214	-0.4404	-0.3080
	[-2.82453]	[-2.82678]	[-0.46071]	[2.27845]	[-2.65683]	[-2.61115]
u (-2)	0.0347	0.1972	0.4150	0.1262	-0.1001	0.2730
	-0.1775	-0.2983	-0.3489	-0.1169	-0.4238	-0.2965
	[0.19533]	[0.66114]	[1.18934]	[1.07963]	[-0.23627]	[0.92087]
i (-1)	0.0693	-0.2244	-0.6333	0.0962	-0.5000	-0.3349
	-0.0749	-0.1258	-0.1472	-0.0493	-0.1788	-0.1251
	[0.92496]	[-1.78296]	[-4.30257]	[1.95065]	[-2.79671]	[-2.67821]
i (-2)	-0.0357	-0.1699	0.1505	0.0659	-0.4607	-0.2429
	-0.0497	-0.0836	-0.0977	-0.0327	-0.1187	-0.0831
	[-0.71809]	[-2.03355]	[1.53983]	[2.01449]	[-3.88037]	[-2.92474]
s (-1)	0.1714	0.1694	0.4212	-0.0358	0.2378	1.0692
	-0.0926	-0.1557	-0.1821	-0.0610	-0.2212	-0.1547
	[1.85020]	[1.08814]	[2.31348]	[-0.58653]	[1.07531]	[6.91162]
s (-2)	0.0409	-0.2864	-0.5049	0.0420	-0.0944	-0.1859
	-0.0939	-0.1579	-0.1846	-0.0618	-0.2243	-0.1569
	[0.43575]	[-1.81422]	[-2.73466]	[0.67863]	[-0.42081]	[-1.18507]
Constant	**0.5326**	0.4640	0.0565	0.1042	-0.4773	-0.5373
	-0.1555	-0.2612	-0.3055	-0.1023	-0.3712	-0.2596
	[3.42625]	[1.77618]	[0.18488]	[1.01837]	[-1.28607]	[-2.06976]
Inf Exp Growth	-0.1142	0.1128	0.4091	0.0159	0.2466	0.0835
	-0.1054	-0.1772	-0.2072	-0.0694	-0.2517	-0.1761
	[-1.08304]	[0.63666]	[1.97424]	[0.22906]	[0.97969]	[0.47391]
R-squared	0.4710	0.3613	0.5936	0.4412	0.3812	0.7136
Adj. R-squared	0.4090	0.2865	0.5460	0.3758	0.3087	0.6800
Sum sq. resids	22.7619	64.2699	87.9217	9.8619	129.7386	63.4805
S.E. equation	0.4528	0.7609	0.8900	0.2981	1.0811	0.7562
F-statistic	7.6010	4.8306	12.4700	6.7423	5.2590	21.2733
Log likelihood	-70.9156	-135.7909	-155.3756	-18.6402	-179.6928	-135.0184
Akaike AIC	1.3587	2.3967	2.7100	0.5222	3.0991	2.3843
Schwarz SC	1.6754	2.7134	3.0268	0.8390	3.4159	2.7011
Mean dependent	0.1621	0.7682	1.3473	0.0024	-0.0106	-1.5110
S.D. dependent	0.5890	0.9009	1.3208	0.3773	1.3003	1.3369

SPF Model Reduced Form VAR

	Forecast Errors of Inflation	Real GDP Growth	M1 Money Growth	Unemp Rt Growth	3-Month T-Bill Growth	Yield Curve Slope Growth
FE (-1)	0.1668	0.1166	0.1080	0.0753	-0.4522	-0.0940
	-0.1020	-0.1708	-0.2028	-0.0668	-0.2432	-0.1696
	[1.63564]	[0.68302]	[0.53256]	[1.12707]	[-1.85927]	[-0.55433]
FE (-2)	0.1616	-0.2872	-0.2759	0.0676	0.9328	0.5844
	-0.0881	-0.1475	-0.1752	-0.0577	-0.2101	-0.1465
	[1.83422]	[-1.94683]	[-1.57488]	[1.17130]	[4.43989]	[3.98965]
y (-1)	-0.0395	0.0747	-0.1034	-0.1103	0.2246	0.1347
	-0.0663	-0.1110	-0.1319	-0.0434	-0.1582	-0.1103
	[-0.59593]	[0.67296]	[-0.78427]	[-2.53981]	[1.41984]	[1.22186]
y (-2)	-0.0912	0.0708	-0.0861	-0.0346	0.1330	0.1817
	-0.0637	-0.1067	-0.1268	-0.0417	-0.1520	-0.1060
	[-1.43045]	[0.66304]	[-0.67889]	[-0.82840]	[0.87478]	[1.71489]
m (-1)	0.0711	-0.1522	0.3972	0.0259	-0.0198	0.0549
	-0.0435	-0.0728	-0.0864	-0.0285	-0.1036	-0.0723
	[1.63561]	[-2.09208]	[4.59602]	[0.91124]	[-0.19144]	[0.76033]
m (-2)	-0.0006	0.1139	0.3275	-0.0398	0.1060	-0.0790
	-0.0433	-0.0724	-0.0860	-0.0283	-0.1032	-0.0719
	[-0.01291]	[1.57220]	[3.80665]	[-1.40614]	[1.02742]	[-1.09868]
u (-1)	**-0.5497**	-0.8477	-0.0641	0.2806	-1.1079	-0.7833
	-0.1827	-0.3059	-0.3634	-0.1196	-0.4357	-0.3038
	[-3.00930]	[-2.77132]	[-0.17634]	[2.34563]	[-2.54281]	[-2.57865]
u (-2)	0.0160	0.2157	0.4820	0.1288	-0.0597	0.2867
	-0.1768	-0.2961	-0.3517	-0.1158	-0.4217	-0.2940
	[0.09033]	[0.72846]	[1.37037]	[1.11188]	[-0.14166]	[0.97496]
i (-1)	0.0510	-0.2063	-0.5676	0.0987	-0.4605	-0.3216
	-0.0730	-0.1223	-0.1452	-0.0478	-0.1741	-0.1214
	[0.69786]	[-1.68713]	[-3.90874]	[2.06424]	[-2.64423]	[-2.64855]
i (-2)	-0.0436	-0.1621	0.1787	0.0670	-0.4437	-0.2371
	-0.0492	-0.0824	-0.0979	-0.0322	-0.1174	-0.0819
	[-0.88535]	[-1.96675]	[1.82503]	[2.07908]	[-3.77838]	[-2.89651]
s (-1)	**0.1804**	0.1604	0.3887	-0.0370	0.2182	1.0626
	-0.0923	-0.1546	-0.1836	-0.0605	-0.2202	-0.1535
	[1.95452]	[1.03763]	[2.11671]	[-0.61231]	[0.99105]	[6.92101]
s (-2)	0.0242	-0.2699	-0.4451	0.0443	-0.0583	-0.1737
	-0.0927	-0.1553	-0.1845	-0.0607	-0.2212	-0.1542
	[0.26143]	[-1.73789]	[-2.41291]	[0.72912]	[-0.26373]	[-1.12645]
Constant	**0.4243**	0.5710	0.4445	0.1193	-0.2435	-0.4582
	-0.1191	-0.1995	-0.2370	-0.0780	-0.2841	-0.1981
	[3.56214]	[2.86208]	[1.87572]	[1.52888]	[-0.85680]	[-2.31303]
R-squared	0.4654	0.3590	0.5793	0.4410	0.3758	0.7130
Adj. R-squared	0.4081	0.2903	0.5342	0.3811	0.3089	0.6823
Sum sq. resids	23.0024	64.5046	91.0089	9.8666	130.8604	63.6089
S.E. equation	0.4532	0.7589	0.9014	0.2968	1.0809	0.7536
F-statistic	8.1241	5.2272	12.8519	7.3621	5.6193	23.1879
Log likelihood	-71.5726	-136.0187	-157.5325	-18.6697	-180.2309	-135.1448
Akaike AIC	1.3532	2.3843	2.7285	0.5067	3.0917	2.3703
Schwarz SC	1.6473	2.6784	3.0227	0.8009	3.3858	2.6645
Mean dependent	0.1621	0.7682	1.3473	0.0024	-0.0106	-1.5110
S.D. dependent	0.5890	0.9009	1.3208	0.3773	1.3003	1.3369

Livingston Model Including Exogenous Inflation Expectations

	Forecast Errors of Inflation	Real GDP Growth	M1 Money Growth	Unemp Rt Growth	3-Month T-Bill Growth	Yield Curve Slope Growth
FE (-1)	0.2097	-0.2442	-0.2368	0.0653	0.5394	-0.4705
	-0.1216	-0.1604	-0.2237	-0.0700	-0.2166	-0.1427
	[1.72526]	[-1.52192]	[-1.05872]	[0.93258]	[2.49027]	[-3.29810]
FE (-2)	**0.4688**	-0.0096	0.1831	0.0343	0.0928	0.1057
	-0.1421	-0.1875	-0.2615	-0.0818	-0.2532	-0.1668
	[3.29891]	[-0.05100]	[0.70007]	[0.41884]	[0.36656]	[0.63382]
y (-1)	0.2146	0.1701	0.1009	-0.1645	0.0961	-0.1047
	-0.1472	-0.1943	-0.2709	-0.0848	-0.2623	-0.1728
	[1.45789]	[0.87560]	[0.37255]	[-1.94099]	[0.36635]	[-0.60620]
y (-2)	**0.3414**	0.2858	0.5245	-0.1321	0.4408	-0.4538
	-0.1466	-0.1935	-0.2698	-0.0845	-0.2613	-0.1721
	[2.32843]	[1.47702]	[1.94372]	[-1.56447]	[1.68705]	[-2.63692]
m (-1)	0.1013	-0.0761	0.4156	0.0434	0.0441	-0.0459
	-0.0723	-0.0955	-0.1331	-0.0417	-0.1289	-0.0849
	[1.40072]	[-0.79701]	[3.12222]	[1.04274]	[0.34192]	[-0.54087]
m (-2)	0.0656	0.0105	0.1769	-0.0418	-0.1387	0.2212
	-0.0701	-0.0925	-0.1290	-0.0404	-0.1249	-0.0823
	[0.93631]	[0.11373]	[1.37116]	[-1.03429]	[-1.11019]	[2.68808]
u (-1)	0.0326	-0.5545	1.1982	0.2506	-0.9489	-0.1421
	-0.3579	-0.4724	-0.6586	-0.2061	-0.6377	-0.4201
	[0.09108]	[-1.17380]	[1.81921]	[1.21579]	[-1.48791]	[-0.33829]
u (-2)	0.1408	0.9984	0.4423	-0.4798	0.8084	-0.6492
	-0.3260	-0.4302	-0.5999	-0.1877	-0.5808	-0.3826
	[0.43193]	[2.32066]	[0.73731]	[-2.55558]	[1.39176]	[-1.69694]
i (-1)	-0.1266	-0.2705	-0.5141	0.1933	-0.5669	0.0943
	-0.1691	-0.2232	-0.3112	-0.0974	-0.3013	-0.1985
	[-0.74847]	[-1.21206]	[-1.65184]	[1.98516]	[-1.88130]	[0.47490]
i (-2)	-0.0393	0.0366	-0.2170	0.0005	-0.0662	-0.0395
	-0.1089	-0.1437	-0.2003	-0.0627	-0.1940	-0.1278
	[-0.36074]	[0.25479]	[-1.08315]	[0.00732]	[-0.34153]	[-0.30914]
s (-1)	**-0.3823**	0.0257	-0.3534	0.0624	0.1667	0.5339
	-0.1976	-0.2608	-0.3636	-0.1138	-0.3521	-0.2319
	[-1.93466]	[0.09863]	[-0.97175]	[0.54860]	[0.47343]	[2.30199]
s (-2)	-0.0632	0.2781	0.7215	-0.1920	0.0583	-0.2154
	-0.1755	-0.2316	-0.3230	-0.1011	-0.3127	-0.2060
	[-0.36023]	[1.20046]	[2.23397]	[-1.89991]	[0.18638]	[-1.04590]
Constant	0.0228	0.5783	-1.8768	0.6993	-1.8687	1.9515
	-0.5177	-0.6832	-0.9527	-0.2981	-0.9224	-0.6076
	[0.04400]	[0.84636]	[-1.97004]	[2.34563]	[-2.02594]	[3.21192]
Inf Exp Growth	-0.2578	0.0324	0.6457	-0.0352	0.3458	-0.2020
	-0.1522	-0.2009	-0.2802	-0.0877	-0.2713	-0.1787
	[-1.69313]	[0.16139]	[2.30477]	[-0.40130]	[1.27492]	[-1.13028]
R-squared	0.5482	0.4530	0.6315	0.5639	0.3780	0.5608
Adj. R-squared	0.4284	0.3079	0.5337	0.4481	0.2130	0.4443

Livingston Model Reduced Form VAR

	Forecast Errors of Inflation	Real GDP Growth	M1 Money Growth	Unemp Rt Growth	3-Month T-Bill Growth	Yield Curve Slope Growth
FE (-1)	0.1751	-0.2398	-0.1501	0.0606	0.5859	-0.4977
	-0.1220	-0.1566	-0.2298	-0.0684	-0.2148	-0.1410
	[1.43459]	[-1.53138]	[-0.65293]	[0.88501]	[2.72700]	[-3.52905]
FE (-2)	**0.4045**	-0.0015	0.3440	0.0255	0.1790	0.0554
	-0.1395	-0.1790	-0.2627	-0.0782	-0.2455	-0.1612
	[2.90048]	[-0.00830]	[1.30956]	[0.32620]	[0.72897]	[0.34365]
y (-1)	0.2246	0.1688	0.0759	-0.1632	0.0827	-0.0969
	-0.1498	-0.1922	-0.2821	-0.0840	-0.2637	-0.1731
	[1.49917]	[0.87844]	[0.26913]	[-1.94283]	[0.31360]	[-0.55985]
y (-2)	**0.3639**	0.2830	0.4682	-0.1291	0.4106	-0.4362
	-0.1487	-0.1909	-0.2801	-0.0834	-0.2618	-0.1719
	[2.44671]	[1.48296]	[1.67160]	[-1.54748]	[1.56832]	[-2.53800]
m (-1)	0.0746	-0.0727	0.4826	0.0398	0.0800	-0.0669
	-0.0719	-0.0923	-0.1354	-0.0403	-0.1266	-0.0831
	[1.03727]	[-0.78832]	[3.56472]	[0.98704]	[0.63176]	[-0.80497]
m (-2)	0.0585	0.0114	0.1948	-0.0427	-0.1291	0.2156
	-0.0713	-0.0915	-0.1342	-0.0400	-0.1255	-0.0824
	[0.82060]	[0.12490]	[1.45153]	[-1.06942]	[-1.02881]	[2.61747]
u (-1)	-0.0009	-0.5503	1.2820	0.2460	-0.9040	-0.1683
	-0.3640	-0.4670	-0.6854	-0.2041	-0.6407	-0.4206
	[-0.00234]	[-1.17820]	[1.87041]	[1.20562]	[-1.41090]	[-0.40018]
u (-2)	0.1016	1.0033	0.5404	-0.4851	0.8609	-0.6799
	-0.3312	-0.4249	-0.6236	-0.1857	-0.5830	-0.3827
	[0.30690]	[2.36111]	[0.86654]	[-2.61260]	[1.47677]	[-1.77671]
i (-1)	-0.2067	-0.2604	-0.3132	0.1824	-0.4593	0.0314
	-0.1654	-0.2122	-0.3114	-0.0927	-0.2911	-0.1911
	[-1.25031]	[-1.22750]	[-1.00601]	[1.96740]	[-1.57802]	[0.16459]
i (-2)	-0.0858	0.0425	-0.1005	-0.0059	-0.0038	-0.0759
	-0.1073	-0.1377	-0.2020	-0.0602	-0.1888	-0.1240
	[-0.79957]	[0.30842]	[-0.49731]	[-0.09791]	[-0.02033]	[-0.61256]
s (-1)	**-0.4444**	0.0335	-0.1979	0.0540	0.2500	0.4853
	-0.1978	-0.2538	-0.3724	-0.1109	-0.3481	-0.2285
	[-2.24689]	[0.13213]	[-0.53139]	[0.48664]	[0.71799]	[2.12340]
s (-2)	-0.0019	0.2703	0.5678	-0.1837	-0.0240	-0.1674
	-0.1749	-0.2244	-0.3294	-0.0981	-0.3079	-0.2021
	[-0.01072]	[1.20462]	[1.72406]	[-1.87285]	[-0.07803]	[-0.82815]
Constant	-0.4690	0.6401	-0.6449	0.6322	-1.2089	1.5662
	-0.4365	-0.5600	-0.8219	-0.2447	-0.7683	-0.5043
	[-1.07457]	[1.14303]	[-0.78463]	[2.58343]	[-1.57351]	[3.10549]
R-squared	0.5218	0.4527	0.5915	0.5624	0.3574	0.5494
Adj. R-squared	0.4070	0.3214	0.4935	0.4574	0.2031	0.4412
Sum sq. resids	39.2717	64.6600	139.2603	12.3459	121.6958	52.4379
S.E. equation	0.8862	1.1372	1.6689	0.4969	1.5601	1.0241
F-statistic	4.5468	3.4466	6.0341	5.3555	2.3170	5.0796
Log likelihood	-74.5052	-90.2124	-114.3792	-38.0542	-110.1324	-83.6127
Akaike AIC	2.7779	3.2766	4.0438	1.6208	3.9090	3.0671
Schwarz SC	3.2202	3.7188	4.4860	2.0630	4.3512	3.5093
Mean dependent	0.3313	1.5382	2.7359	0.0095	-0.0043	1.5081
S.D. dependent	1.1509	1.3804	2.3450	0.6746	1.7477	1.3700

APPENDIX F
PAIRWISE GRANGER CAUSALITY TESTING

Survey of Professional Forecasters (Sample Period 1969-2001)

Exclude	Chi-sq	df	Prob.
AGDP1	7.473790	4	0.1129
AM1G	9.399682	4	**0.0518**
D(AUNEMP1)	18.40765	4	**0.0010**
D(ATBILL1)	6.448741	4	0.1680
YCURVE	10.89914	4	**0.0277**
All	73.05190	20	0.0000

Null Hypothesis:	Obs	F-Statistic	Probability
AGDP1 does not Granger Cause FEINF	125	4.03629	**0.00422**
FEINF does not Granger Cause AGDP1		5.53753	**0.00041**
AM1G does not Granger Cause FEINF	124	1.14766	0.33780
FEINF does not Granger Cause AM1G		1.92344	0.11121
AUNEMP1 does not Granger Cause FEINF	125	6.65129	**7.4E-05**
FEINF does not Granger Cause AUNEMP1		4.57539	**0.00182**
ATBILL1 does not Granger Cause FEINF	125	5.22989	**0.00066**
FEINF does not Granger Cause ATBILL1		3.01471	**0.02085**
YCURVE does not Granger Cause FEINF	124	4.75131	**0.00139**
FEINF does not Granger Cause YCURVE		3.35301	**0.01232**

Survey of Professional Forecasters (Sample Period 1983-2001)

Exclude	Chi-sq	df	Prob.
AGDP1	0.762888	4	0.9434
AM1G	3.978103	4	0.4090
D(AUNEMP1)	6.643081	4	0.1560
D(ATBILL1)	6.267559	4	0.1800
YCURVE	8.158115	4	**0.0860**
All	27.74800	20	0.1155

Null Hypothesis:	Obs	F-Statistic	Probability
AGDP1 does not Granger Cause FEINF	73	0.29836	0.87797
FEINF does not Granger Cause AGDP1		2.15598	**0.08403**
AM1G does not Granger Cause FEINF	73	0.89707	0.47104
FEINF does not Granger Cause AM1G		3.53236	**0.01147**
AUNEMP1 does not Granger Cause FEINF	73	4.24866	**0.00412**
FEINF does not Granger Cause AUNEMP1		1.35033	0.26114
ATBILL1 does not Granger Cause FEINF	73	0.59622	0.66666
FEINF does not Granger Cause ATBILL1		0.71014	0.58799
YCURVE does not Granger Cause FEINF	72	2.91563	**0.02811**
FEINF does not Granger Cause YCURVE		0.60665	0.65931

SPF Pairwise Granger Causality Test including Relative Price of Energy 1969-2001

Exclude	Chi-sq	df	Prob.
AGDP1	5.604865	4	0.2307
AM1G	10.11205	4	**0.0386**
D(AUNEMP1)	9.920655	4	**0.0418**
D(ATBILL1)	6.538784	4	0.1624
YCURVE	9.204604	4	**0.0562**
D(CPIEN)	9.493439	4	**0.0499**
All	86.64030	24	0.0000

SPF Pairwise Granger Causality Test including Relative Price of Energy 1983-2001

Exclude	Chi-sq	df	Prob.
AGDP1	0.456635	4	0.9776
AM1G	2.946995	4	0.5667
D(AUNEMP1)	4.806885	4	0.3077
D(ATBILL1)	4.941763	4	0.2933
YCURVE	5.664914	4	0.2256
D(CPIEN)	0.286676	4	0.9907
All	25.84239	24	0.3612

Livingston Survey (Sample Period 1969-2000)

Exclude	Chi-sq	df	Prob.
D(100*LOG(AGDPLVL))	7.604963	2	**0.0223**
D(100*LOG(AM1SL))	5.118776	2	**0.0774**
D(AUNEM)	0.094378	2	0.9539
D(ATBILL)	1.655985	2	0.4369
YCURVE	9.624795	2	**0.0081**
All	30.89920	10	**0.0006**

Null Hypothesis:	Obs	F-Statistic	Probability
AGDP does not Granger Cause FEINFSA	76	2.85366	**0.03022**
FEINFSA does not Granger Cause AGDP		3.13970	**0.01991**
AM1GR does not Granger Cause FEINFSA	76	1.16293	0.33507
FEINFSA does not Granger Cause AM1GR		2.73394	**0.03600**
AUNEM does not Granger Cause FEINFSA	76	2.00456	**0.10383**
FEINFSA does not Granger Cause AUNEM		3.25280	**0.01688**
ATBILL does not Granger Cause FEINFSA	76	3.05858	**0.02241**
FEINFSA does not Granger Cause ATBILL		0.91248	0.46189
YCURVE does not Granger Cause FEINFSA	76	3.38110	**0.01400**
FEINFSA does not Granger Cause YCURVE		1.34240	0.26342

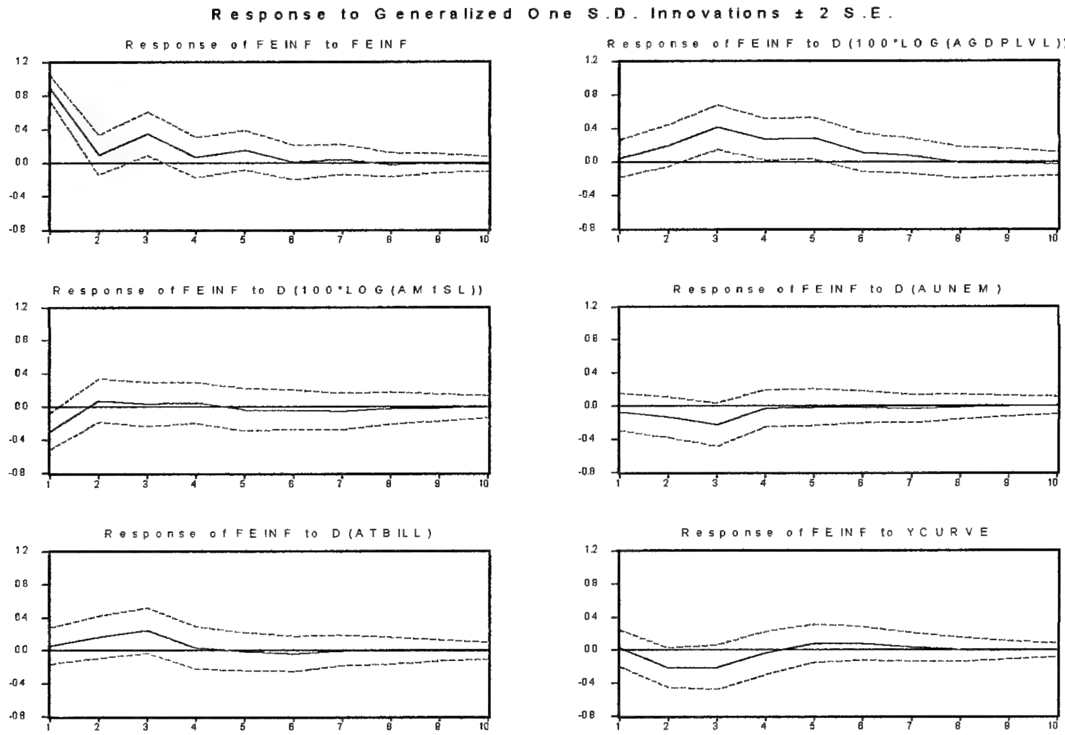
Livingston Survey (Sample Period 1983-2000)

Exclude	Chi-sq	df	Prob.
AGDP	0.130307	2	0.9369
AM1GR	1.072762	2	0.5849
D(AUNEM)	1.246540	2	0.5362
D(AFF)	1.313550	2	0.5185
YCURVE	2.554143	2	0.2789
All	5.320059	10	0.8688

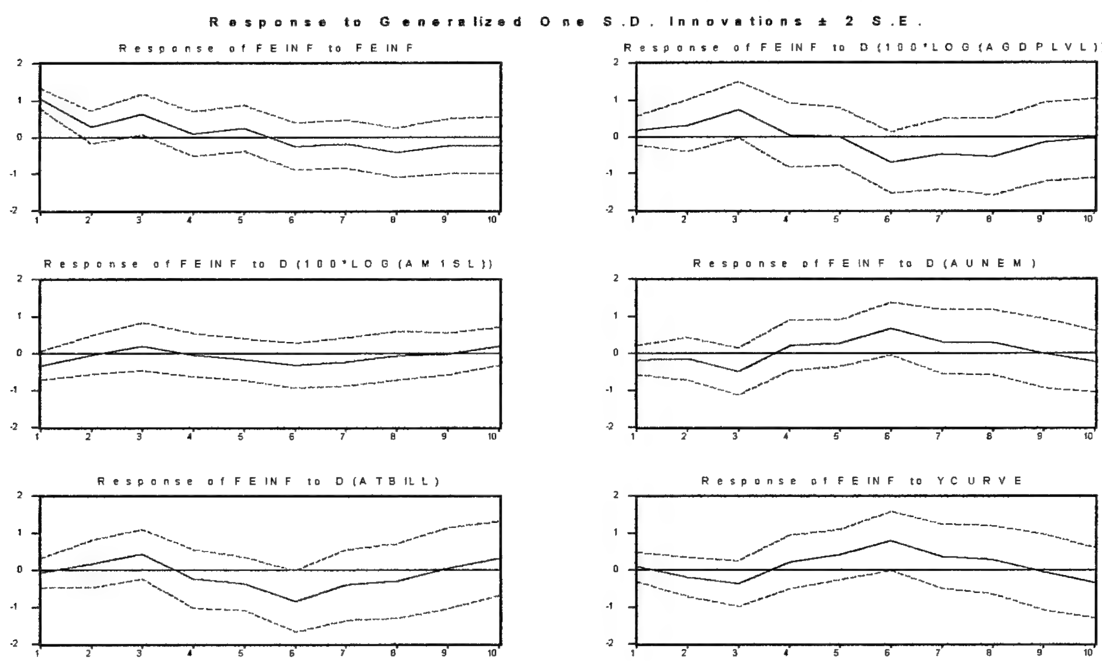
Null Hypothesis:	Obs	F-Statistic	Probability
AGDP does not Granger Cause FEINFSA	35	0.48362	0.74755
FEINFSA does not Granger Cause AGDP		4.51633	**0.00665**
AM1GR does not Granger Cause FEINFSA	35	0.07983	0.98784
FEINFSA does not Granger Cause AM1GR		3.82094	**0.01425**
AUNEM does not Granger Cause FEINFSA	35	1.06430	0.39403
FEINFSA does not Granger Cause AUNEM		3.63071	**0.01767**
ATBILL does not Granger Cause FEINFSA	35	0.22363	0.92275
FEINFSA does not Granger Cause ATBILL		0.81188	0.52906
YCURVE does not Granger Cause FEINFSA	35	1.80924	0.15734
FEINFSA does not Granger Cause YCURVE		0.82162	0.52325

APPENDIX G
IMPULSE RESPONSE FUNCTION ANALYSIS

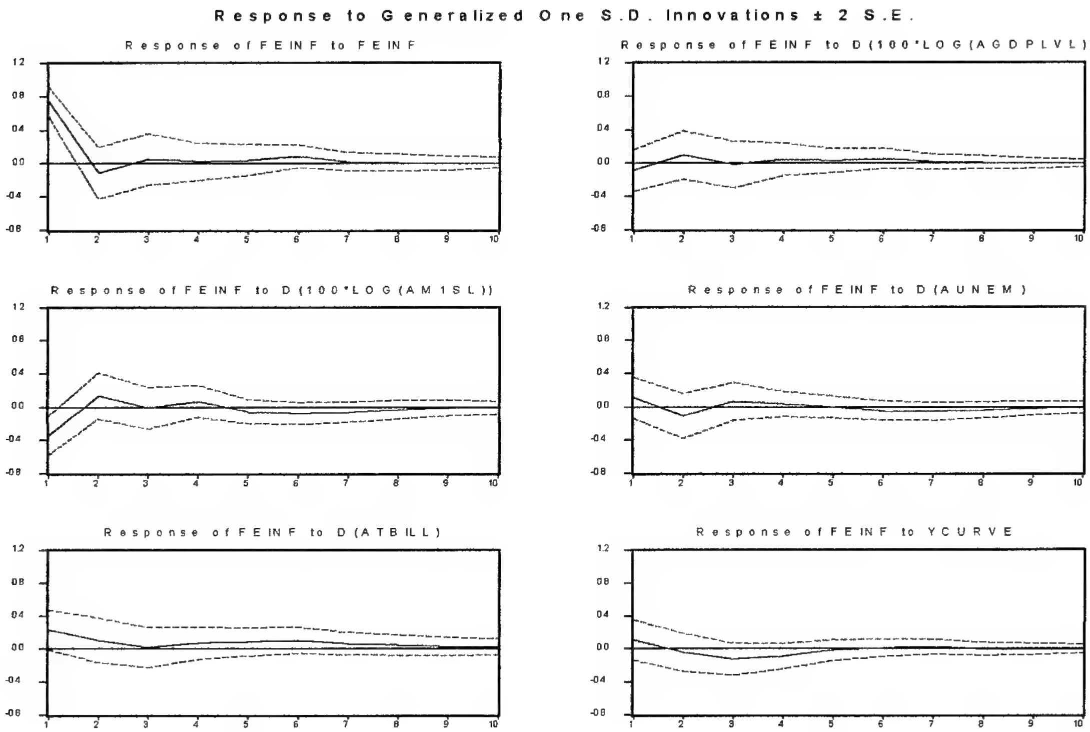
Livingston Model IRF – Reduced Form VAR 1969-2000



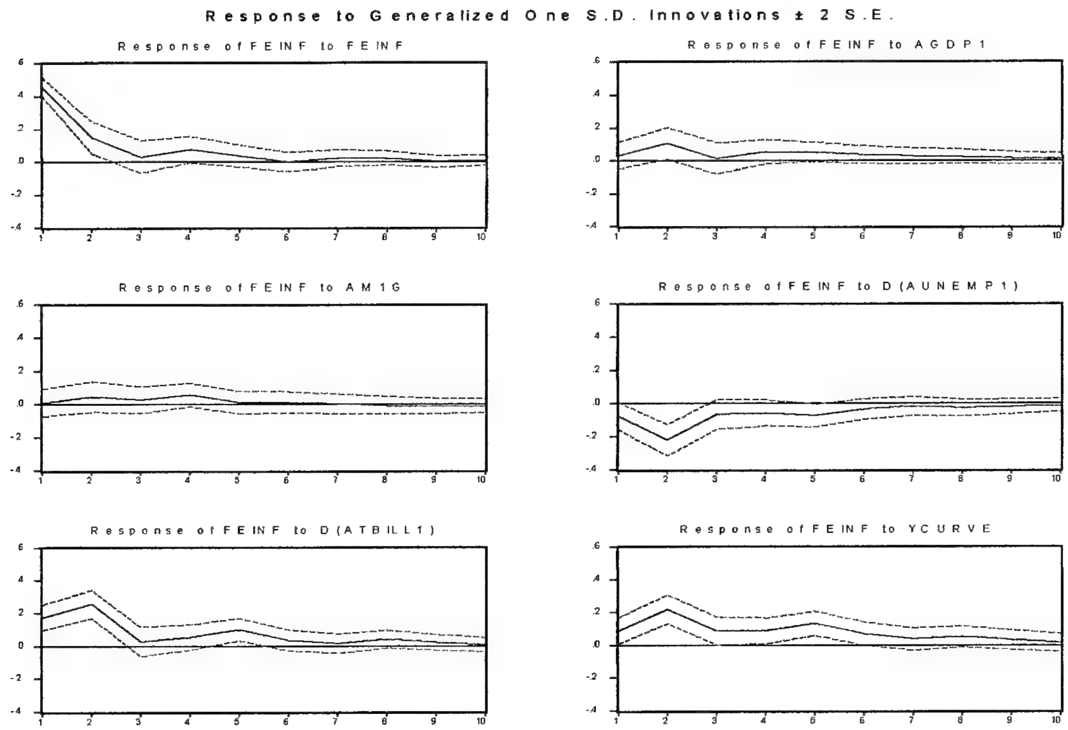
Livingston Model IRF – Reduced Form VAR 1969-1983



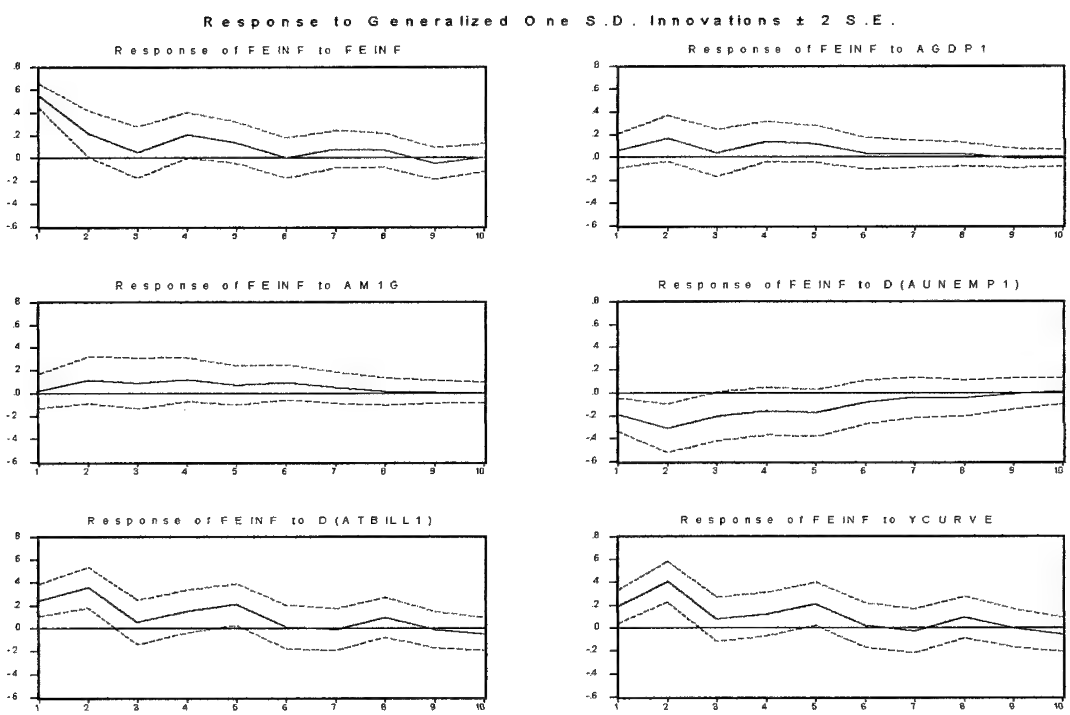
Livingston Model IRF – Reduced Form VAR 1983 - 2000



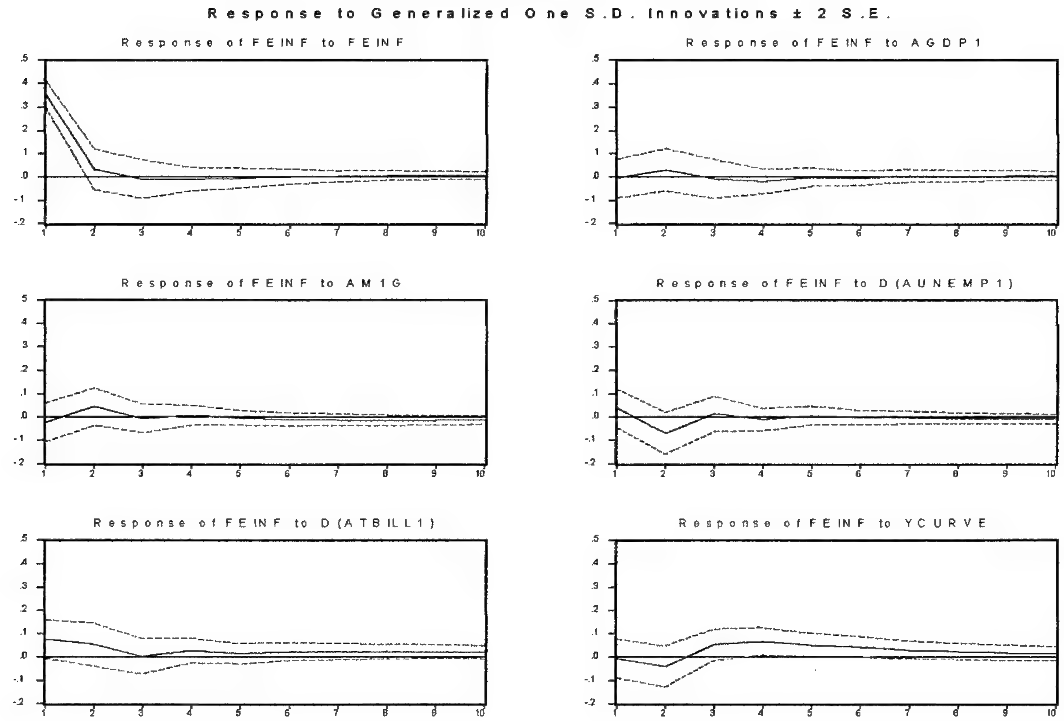
SPF Model IRF – Reduced Form VAR 1969-2000



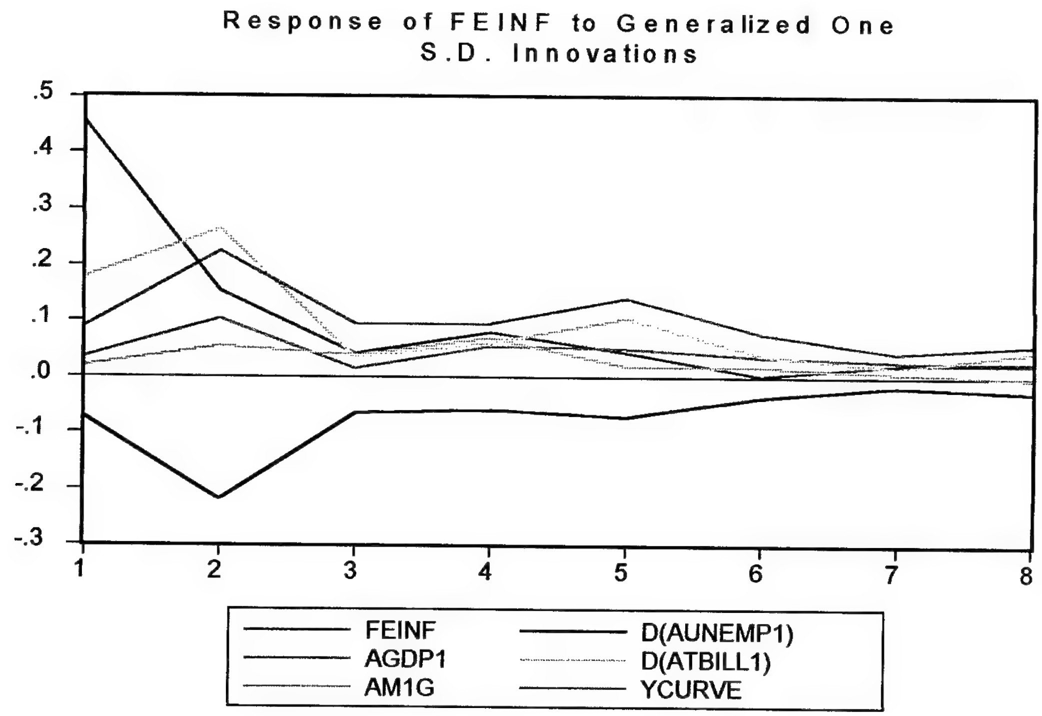
SPF Model IRF – Reduced Form VAR 1969-1983



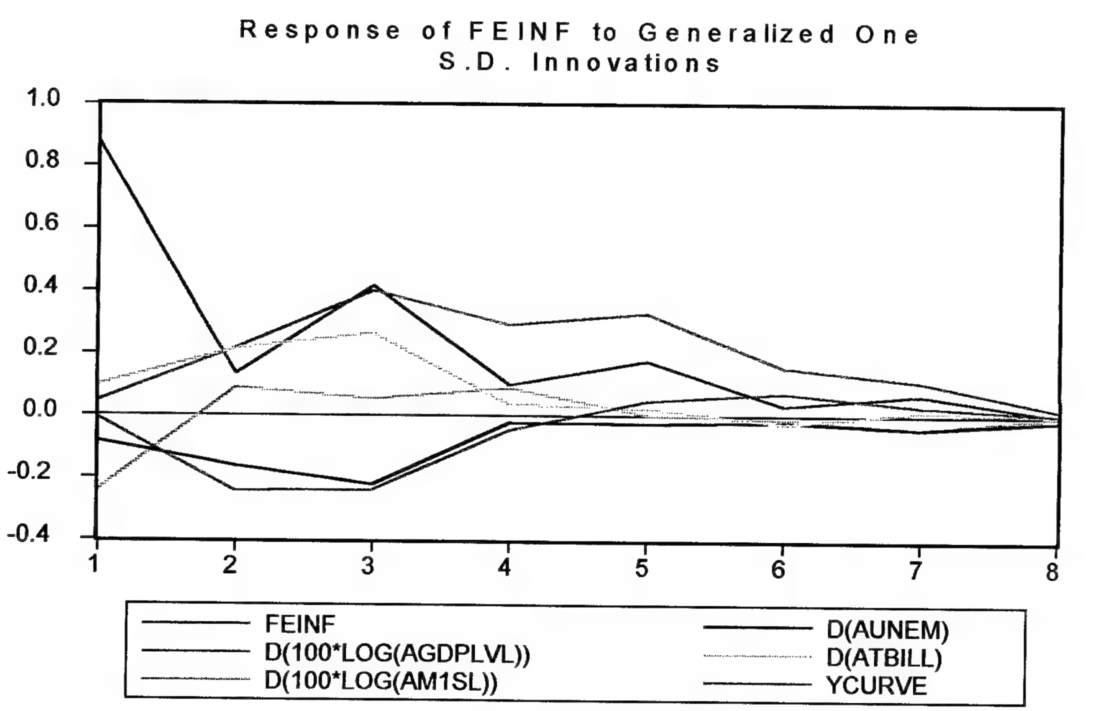
SPF Model IRF – Reduced Form VAR 1983 – 2000



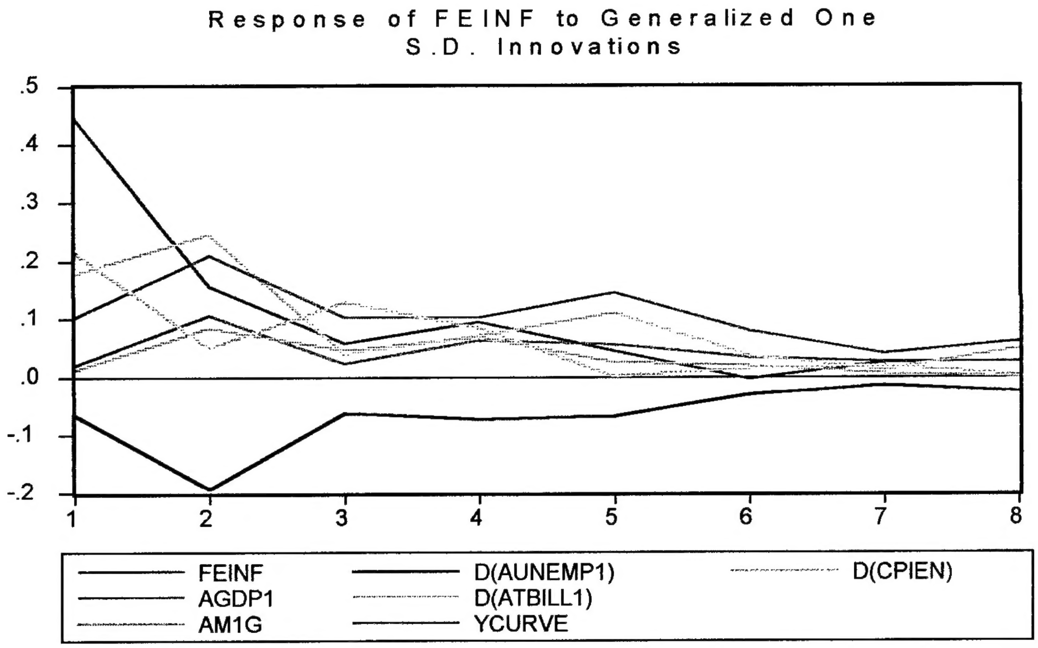
SPF Model IRF – Reduced Form VAR 1969 – 2001 Combined Response Graph



Livingston Model IRF – Reduced Form VAR 1969 - 2000 Combined Response Graph

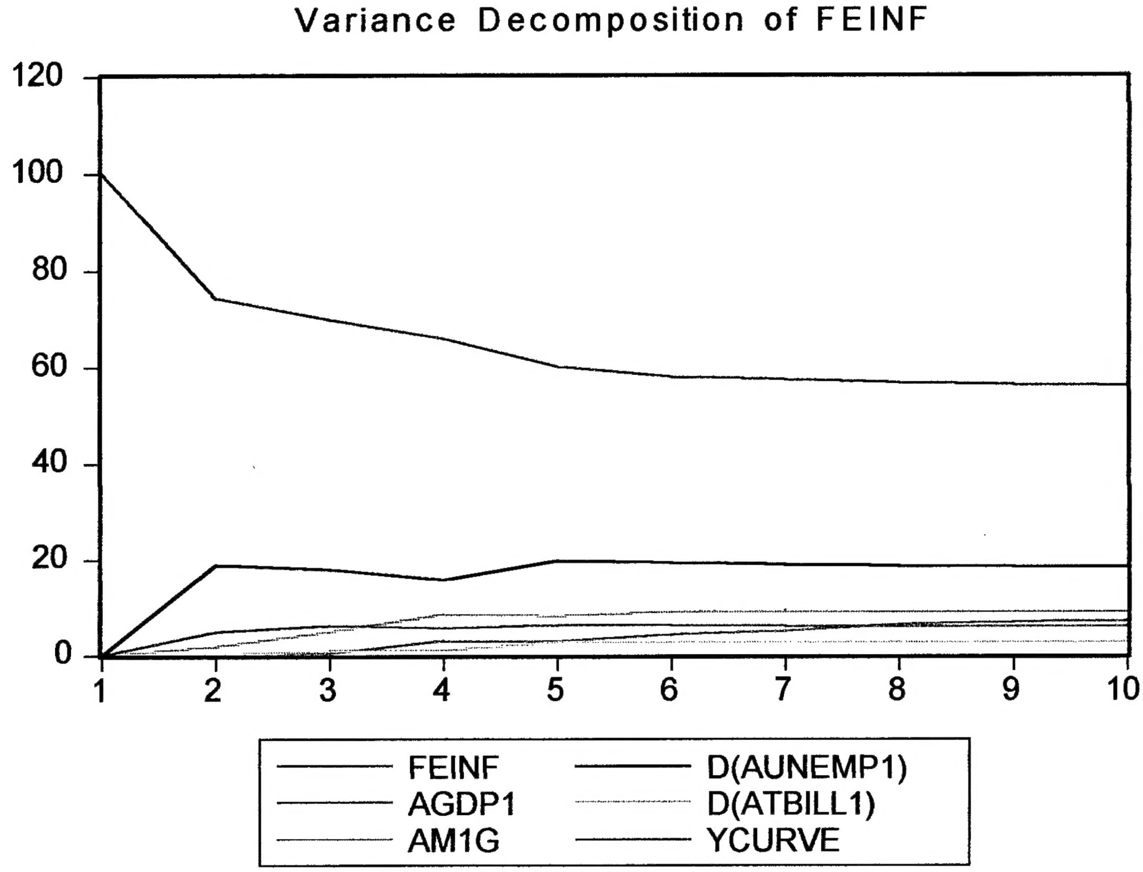


SPF Model IRF – Reduced Form VAR 1969 – 2001 Combined Response Graph
(Including the relative price of energy)



APPENDIX H
VARIANCE DECOMPOSITION
OF
FORECAST ERRORS

SPF Forecast Error Variance Decomposition



Period	S.E.	FEINF	AGDP1	AM1G	D(AUNEMP1)	D(ATBILL1)	YCURVE
1	0.423196	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.520040	74.30684	0.062903	1.807408	18.87725	0.157801	4.787795
3	0.536890	69.81854	0.338277	4.805793	18.01805	0.922542	6.096799
4	0.574460	65.87699	3.015270	8.564185	15.76995	1.085801	5.687798
5	0.616138	60.05848	2.888821	8.173819	19.80918	2.771208	6.298497
6	0.628338	58.01207	4.282651	9.019802	19.44938	2.935675	6.300424
7	0.636918	57.49138	5.091868	9.354444	19.03594	2.881177	6.145188
8	0.647391	56.81443	6.419583	9.136909	18.73377	2.871227	6.024081
9	0.650287	56.36992	6.996393	9.059508	18.68868	2.856134	6.029362
10	0.651824	56.24324	7.124346	9.021195	18.60893	2.881330	6.120951

Cholesky Ordering: FEINF D(AUNEMP1) YCURVE AM1G AGDP1 D(ATBILL1)

SPF Forecast Error Variance Decomposition Including the Relative Price of Energy